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SURVEY

# A Systematic Literature Review on Plant Disease Detection: Motivations, Classification Techniques, Datasets, Challenges, and Future Trends

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**ABSTRACT** Plant pests and diseases are a significant threat to almost all major types of plants and global food security. Traditional inspection across different plant fields is time-consuming and impractical for a wider plantation size, thus reducing crop production. Therefore, many smart agricultural practices are deployed to control plant diseases and pests. Most of these approaches, for example, use vision-based artificial intelligence (AI), machine learning (ML), or deep learning (DL) methods and models to provide disease detection solutions. However, existing open issues must be considered and addressed before AI methods can be used. In this study, we conduct a systematic literature review (SLR) and present a detailed survey of the studies employing data collection techniques and publicly available datasets. To begin the review, 1349 papers were chosen from five major academic databases, namely Springer, IEEE Xplore, Scopus, Google Scholar, and ACM library. After deploying a comprehensive screening process, the review considered 176 final studies based on the importance of the method. Several crops, including grapes, rice, apples, cucumbers, maize, tomatoes, wheat, and potatoes, have tested mainly on the hyperspectral imagery and vision-centered approaches. Support Vector Machines (SVMs) and Logistic regression (LR) classifiers demonstrated an increased accuracy in experiments compared to traditional classifiers. Besides the image taxonomy, disease localization is depicted in these approaches as a bottle neck to disease detection. Cognitive CNNs with attention mechanisms and transfer learning are showing an increasing trend. There is no standard model performance assessment though the majority use accuracy, recall, precision, F1 Score, and confusion matrix. The available 11 datasets are laboratory and in-field based, and 9 are publicly available. Some laboratory-based datasets are considerably small, making them impractical in experiments. Finally, there is a need to avail models with fewer parameters, implementable on small devices and large datasets accommodating several crops and diseases to have robust models.

**INDEX TERMS** Convolutional neural networks, deep learning, image processing, machine learning, plant disease detections.

## ABBREVIATIONS

| | |
|---|---|
| ABCK | Artificial Bee Colony Method |
| ACM | Association for Computing Machinery |
| AI | Artificial Intelligence |
| ANN | Artificial Neural Networks |
| ASDE | Advanced Segmented Dimension Extraction |
| CART | Classification and Regression Tree |
| CBAM | Convolution Block Attention Module |
| CBAM | Carbon Border Adjustment Mechanism |
| CGAN | Conditional Generative Adversarial Network |
| CNN | Convolutional Neural Network |

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| | |
|---|---|
| DL | Deep Learning |
| DP | Disease Prediction |
| DT | Decision Trees |
| FN | False Negatives |
| FP | False Positives |
| FSL | Few-Shot Learning |
| HIoT | Heterogeneous Internet of Things |
| IEEE | Institute of Electrical and Electronics Engineers |
| IoT | Internet of Things |
| IP | Image Processing |
| KNN | K-Nearest Neighbors |
| MAE | Mean Absolute Error |
| mAP | Mean Average Precision |
| NB | Naïve Bayes |
| NB | Naive Bayes classifier |
| OLPSO | Orthogonal learning particle swarm optimization |
| PDD | Plant Disease Detection |
| PDI | Plant Disease Identification |
| PVD | Plant Village Dataset |
| RAN | Residual Attention Network |
| RF | Random Forest |
| RF | Random Forest |
| RMSE | Root Mean Square Error |
| RPN | Risk Priority Number |
| RPN | Region Proposal Network |
| RSE | Relative Standard Error |
| SCNN | Sequential Convolutional Neural Network |
| SCNN | Shallow Convolutional Neural Network |
| SIFT | Scale Invariant Feature Transform |
| SMO | Spider monkey optimization |
| SPAM | Subtractive pixel adjacency model |
| SSD | Single-shot detector |
| SVM | Support Vector Machines |
| TF | Transfer Learning |
| TN | True Negatives |
| TP | True Positives |
| UAV | Unmanned Aerial Vehicle |
| UN | United Nations |
| WHO | World Health Organization |
| XGB | Extreme gradient boosting |

## I. INTRODUCTION

Plant pathogens and pests cause substantial reduction in plant production depending on adverse seasonal and environmental conditions leading to economic and social losses. Contemporary pests and pathogen management depend profoundly on pesticide application, for example, herbicides, fungicides, and insecticides [1], [2], [3], [4], [5]. According to the United Nations' global goals, zero hunger is approximated to be accomplished by 2030 [6]. Early plant disease detection and classification significantly increase food security to attain the target. According to the World Health Organization (WHO), as of 2021, the total global population is approximately 7.837 billion, indicating that the demand for food increases along with the global population. Prioritizing food production is vital to addressing the issue of global hunger since the UN reported that global hunger numbers rose to as much as 828 million in 2021 [3], [7], [8], [9], [10]. Farmers have widely used chemicals, for instance, insecticides and herbicides, to man- age plant diseases and pests and increase crop yields. In the short run, these chemicals increase plant yields without decreasing crop quality. However, in the long run, for instance, in terms of health, chemicals such as herbicides pollute the ground where they are used and the environment in general. This is because of their chemical toxicity, which poses severe health risks and causes nearly three hundred thousand deaths annually, as demonstrated in [11], [12], [13], and [14].

Detecting plant diseases early can minimize the use of hazardous chemicals in plant growth and protection. For example, IoT methods for detecting and diagnosing plant health status have been proposed, as have recent artificial intelligence (AI) methods such as deep and machine learning and image processing (IP) centered disease detection [15], [16], [17], [18]. Various methods have been presented in recent years to appreciate AI's increased agricultural application, for example, deep learning (DL) approaches in building advanced AI models for plant disease detection [17], [18], [19], [20]. Despite advances in AI-based methods, plant disease detection in natural environments remains an issue. Drones are being used to monitor plant health to track diseases. As a result, compared to digital cameras, these semi- or autonomous aircraft provide robust and dependable vision methods that can be used on various crops [21].

This study provides a detailed overview of the most recent disease identification and PDD approaches, focusing on the most used AI (ML and DL) and IP algorithms for disease identification. Moreover, it systematically evaluates the limitations, strengths, and significant traits of these methods in real-world applications. A search of five major academic research databases, namely Springer, IEEE Xplore, Scopus, Google Scholar, and ACM, yielded 1349 papers for this review. Some keywords that were used during the search include "disease classification," "disease identification," "crop disease detection," "PDD," "ML," "DL," and "IP." According to the significance of the recent surveys, the prominence of the approach, performance in PDD, and the used datasets, 176 studies were selected for the study.

The remainder of this systematic literature review is organized into six sections: Section II presents a summary of the study background and the motivations. Section III summarizes the current survey literature in the PDD field and the rationale for this study. Section IV depicts the essentials of the survey process, including review questions, followed by the method of approach. An analysis of the current studies on PDDs and localization is presented in Section V. Lastly, the conclusion of the review and the recommendations on future trends are demonstrated in Section VI.

## II. STUDY BACKGROUND

Plant diseases have a global effect on plant production. Therefore, farmers are supposed to attain expert knowledge and

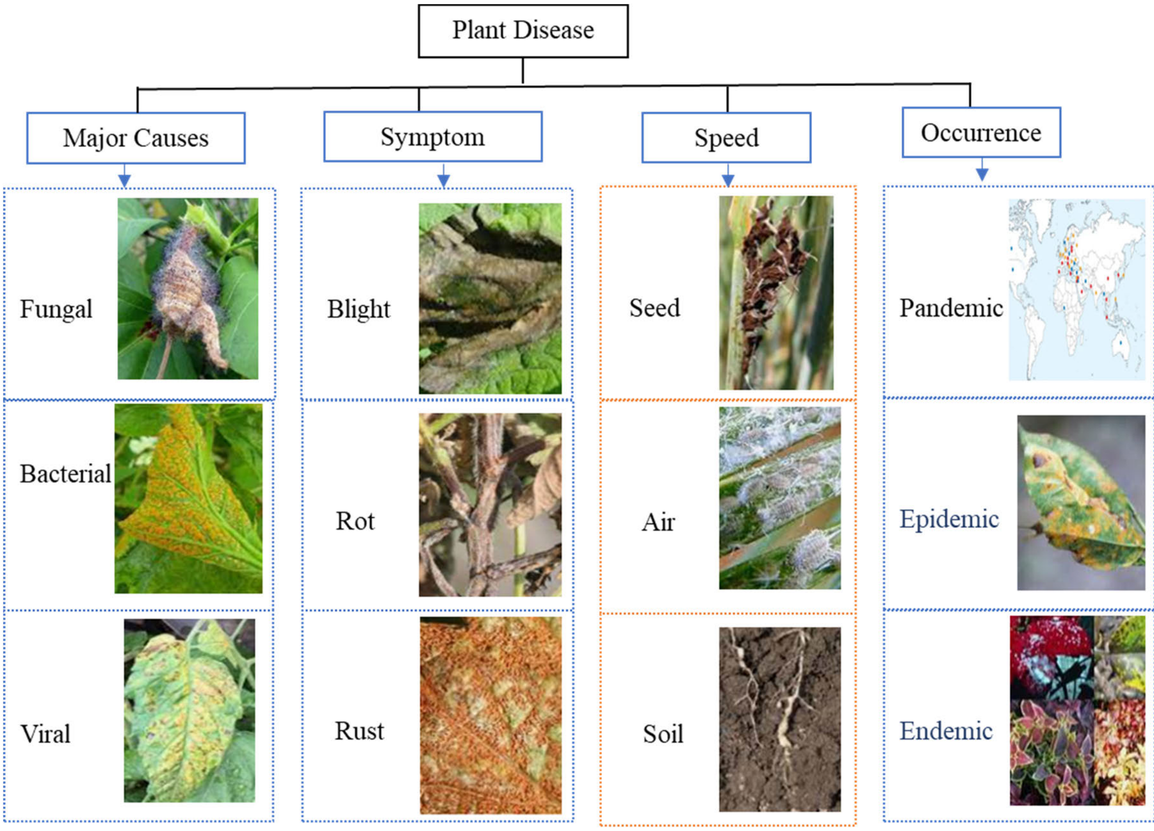



**FIGURE 1.** Plant disease classification.

thorough training to distinguish early plant pests or viral symptoms and take appropriate action to prevent disease continuity. PDD control can help economic development by reducing hunger and saving the environment through reduced chemical fertilizer utilization. Environmental factors primarily cause plant diseases, and pathogens (like bacteria, worms, viruses, fungi, and protozoa) are defined as diseases in plant pathology. Several plant diseases commonly occur because of a variety of factors. For instance, depending on its nature, soil, seed, or air type, it can be caused by a pandemic, epidemic, or endemic. Other factors include symptoms and significant causes such as blight, rots, and viruses, as shown in Fig. 1. Early symptoms are essential in PDD because conventional traits for identifying in-field diseases are based on several factors, including the type of disease, its color, pattern, appearance, and location on the plant. These symptoms on various sections of plants, like the stems, fruits, and leaves, among others, are primarily utilized in PDD. Farmers and agricultural experts use traditional surveillance to identify disease categories. High-tech agricultural systems that use vision-based learning approaches for PDD can effectively increase crop yields. There has been an improvement in efficiency in identifying plant diseases using AI for early diagnosis and smart inspection automation. Few valid case studies in third-world countries use automatic approaches in agriculture. Despite the contributions of the remarkable endeavors available, a few factors continue to make real-time PDD complex. The main objective of this review is to present techniques, available datasets, and challenges in plant disease detection that need to be addressed to develop comprehensive, intelligent agricultural methods for monitoring and diagnosing early plant detection. The following are the main other contributions to this review:

- Based on the current surveys, this review is the first systematic study on image-based PDD approaches covering both localization and disease classification.
- The study shows a complete data collection and preprocessing strategy for PDD used in academia and business.
- The study also looks at three crucial methods: deep learning, machine learning, and image processing relating to plant diseases.
- Deep learning methods and their applicability to IoT-centered smart farming solutions are also investigated.
- All public datasets that can be used with this research paradigm are examined in the study, and their details are given.

## III. RELATED LITERATURE

Several studies on ML and DL approaches used in agriculture have been evaluated, leaving a gap to comprehensively examine image-centered plant disease detection. Most recently, a review was made of the imperativeness of existing PDD methods and included segmentation, classification, localization, and disease techniques [22]. The study [23] concentrated on the performance of the CNN method in PDD, primarily on fruits, vegetables, and various plants. Other studies, like [24], focused on barley, maize, rice, soy- beans, and wheat and compared the benefits and drawbacks of various IPs, segmentations, extractions, feature selections, and classifications. The main goal of this survey is to demonstrate the use of electric impedance spectroscopy, hyperspectral imaging, and fluorescence spectroscopy, among other things.

This showed that many problems still need to be solved, such as real-time inspection of a larger farmyard. The authors compared the performance of various approaches based on feature extraction, classification, segmentation, and preprocessing using IP. They noticed that the segmentation strategy known as "k-means" was frequently used to identify plant diseases [25]. A comprehensive review of existing approaches in the early 2000s was conducted, with implications for fully automated PDD and identification using digital approaches [26]. Investigation of the literature was done with three different methodologies, namely, image processing, deep and machine learning in one of the early reviews on PDD, namely, molecular, spectral, and biogenic compound profiling [27]. The authors revealed that using autonomous agricultural aircraft, imaging, and spectroscopic methods can be merged to aid in detection and identification at an early stage; corresponding to their research, they concluded that the 3D dataset is more efficient in early PDD.

Studies [28] and [29] generally focused on the CNN model as it is used in the PDD and concluded by showing that there is still a gap to fill in improving the methods when considering identical visual environments, respectively. Existing surveys have covered a few strategies and highlighted numerous significant problems, but there is a need to assess the in-situ application potential of various techniques [30]. Since datasets are a vital part of making artificial intelligence applications, it is not impractical to ignore data collection techniques and the fact that there are public data sources.

The use of datasets in assessing the development of field studies is widely appreciated. It begins with data capture techniques and publicly available datasets. This work delivers a thorough assessment of vision-based ML strategies for PDD. In addition to a brief overview of the devices utilized for data capture, the study describes the capture conditions, the regions from which datasets are obtained, and preprocessing procedures. The review also discusses the various kinds of openly accessible datasets that scientists in the field use. In addition, this review examines the influence of current trends in DL, localization, TF, and attention processes, together with lightweight approaches in PDD. In addition to the necessity for additional research on TF strategies, the impact of lightweight models in real- time applications must also be investigated. Also, CNNs have surfaced as a potential approach in recent research years. Their suitability for in-situ identification of plant diseases must be evaluated. There is no available study focusing on attention and localization strategies for PDD after an exhaustive search. This review provides a logical evaluation of existing methodologies with intentions and a methodical explanation of several classifications and localization-based PDD methods. An example of existing studies with various goals is demonstrated in Table 1, which shows the used method, current citation, and study scope.

**TABLE 1. Recent surveys on plant disease classification and detection.**

| Method | Citation as of Dec 2022 | Scope | Reference |
|---|---|---|---|
| Machine learning and deep learning | 18 | Data preparation, collection, and recently applied technologies | [22] |
| Deep learning | 56 | Changing the image background and symptoms Variations and CNN models with a shortage of datasets | [23] |
| Deep learning | 70 | CNN is used for PDD tasks. | [24] |
| Deep learning | 69 | model, sources, pre-processing, and evaluation strategies employed for CNN methods. | [25] |
| Deep learning | 76 | DNNs and superficial networks | [26] |
| Machine and deep learning | 32 | Classifications, segmentations, and localization | [27] |
| Deep learning | 37 | CNN: fruits and various plant diseases. | [28] |
| Machine learning and image processing | 33 | Feature extraction, feature selection, segmentation, and classification techniques | [29] |
| Image Processing | 61 | Different spectroscopy datasets for evaluation | [30] |
| Machine learning and image processing | 241 | Detection of citrus diseases | [31] |
| Image Processing | 440 | The visual appearance of symptoms, differing backgrounds, capturing situations, and real-time assessment | [32] |
| Image Processing | 1203 | Plant volatile organic compound profiling, imaging, and spectroscopic molecular methods | [33] |

## IV. REVIEW PROCEDURE

This study evaluates vision-based PDD and identification methods and early demonstrated IP, ML, and DL PDD methods. In addition, the study addresses early and modern disease categorization and localization approaches. This systematic review follows the study presented in [34] on the planning, execution, and evaluation of the review process. Planning establishes the review questions, information on sources, selection criteria, and evaluation quality procedures. Research articles were selected using keywords from relevant academic databases throughout the execution process. The summary step critically evaluates the existing techniques, their strengths and weaknesses, and their suitability for actual in-field implementation.

### A. REVIEW QUESTIONS

Besides advancing PDDs and symptom analysis, premature plant disease identification (PDI) remains challenging. Researchers have analyzed PDI, visual resemblance, and crop performance. The necessity for IoT-based cyber physical agricultural systems raises the following question: "What is the present state of classical IP, DL, and ML methods for PDDs in terms of their application in the field?" Other supplementary questions are also included to assist in the discovering of appropriate PDD technologies. The basis of this review process comprises the relevant research questions listed below.

- RQ1: Which plants and artificial intelligence methods are the best for disease identification?
- RQ2: How does the practice of localization help farmers find ways to treat plant diseases in real-time?
- RQ3: What are some more innovative approaches to the detection of plant diseases?
- RQ5: What kind of impact do lightweight CNNs have on the process of identifying plant diseases or detecting them?
- RQ6: How effective have the techniques based on transfer learning been in the identification of disease?
- RQ7: In what ways do conventional image processing and machine learning approaches add to the complexity of detecting plant diseases?
- RQ8: Is there an adequate public dataset for machine and deep learning in the PDD and identification?
- RQ9: Are researchers modeling plant disease detection techniques that employ data collection and preprocessing approaches?

### B. SEARCHING APPROACH

Within this study, the searched research papers were obtained using different search strings, namely, "crop disease detection," "plant disease identification," "plant disease classification," "ML," "DL," and "IP," from five top known academic databases, including ACM, Springer, Scopus, IEEE Xplore, and Google Scholar. After retrieving articles from several search databases, we based our decision on the research selection criteria to decide which articles should be included or excluded, as demonstrated in Table 2.

**TABLE 2. Selection criteria.**

| Considered studies | Unconsidered studies |
|---|---|
| Employed DL techniques | The original language was not English. |
| Employed IP techniques | Short memos |
| Employed ML techniques | Absence of full text |
| Articles published between 2012 and 2022 | Articles without relevant facts |

**TABLE 3. Quality assessment measures.**

| Question | Quality Scores | |
|---|---|---|
| Is future direction mentioned in the study? | 1.0 | Yes |
| | 0.5 | Partly |
| | 0.0 | Nil |
| Does the study demonstrate performance assessment? | 1.0 | comprehensive details with assessment measures |
| | 0.5 | Deficient details |
| | 0.0 | Nil quantitative findings |
| Does the study contain a methodology? | 1.0 | Specifics are presented with appropriate information. |
| | 0.5 | Limited details are illustrated. |
| | 0.0 | No sections are present. |
| Does the study contain results and datasets? | 1.0 | Specifics are presented with appropriate information. |
| | 0.5 | Limited details are illustrated. |
| | 0.0 | No sections are present. |
| Are the papers published before 2020 supported by citations? | 1.0 | Acceptable citations |
| | 0.5 | Fewer citations |
| | 0.0 | There is no citation at all. |

### C. SELECTION AND QUALITY EVALUATION

Articles that were not initially written in English or did not include all relevant facts were not considered. Furthermore, studies that were discovered to be of high quality because of the search were removed from the compilation. The quality chosen for further review was determined based on the score achieved using the quality assessment benchmarks. The five questions shown in Table 3 were used as the primary means to sort out the overall quality of the article. The scores were given to the articles to determine whether they satisfied inclusion requirements (1 represented "yes," 0.5 illustrated "partial," and 0 showed "nil"). The final score was found by adding all the points given for each question about a specific article. In addition, the articles are sorted according to the quality score to find the relevant articles to the search. Based on the scores, 176 studies published between 2012 and 2022 were chosen to be included in this review. The identification of plant diseases was approached in these research publications using several techniques, including IP, DL, and ML.

### D. EXTRACTION OF ARTICLES

The abstracts and titles of the publications were initially reviewed, and then the complete contents of the articles were

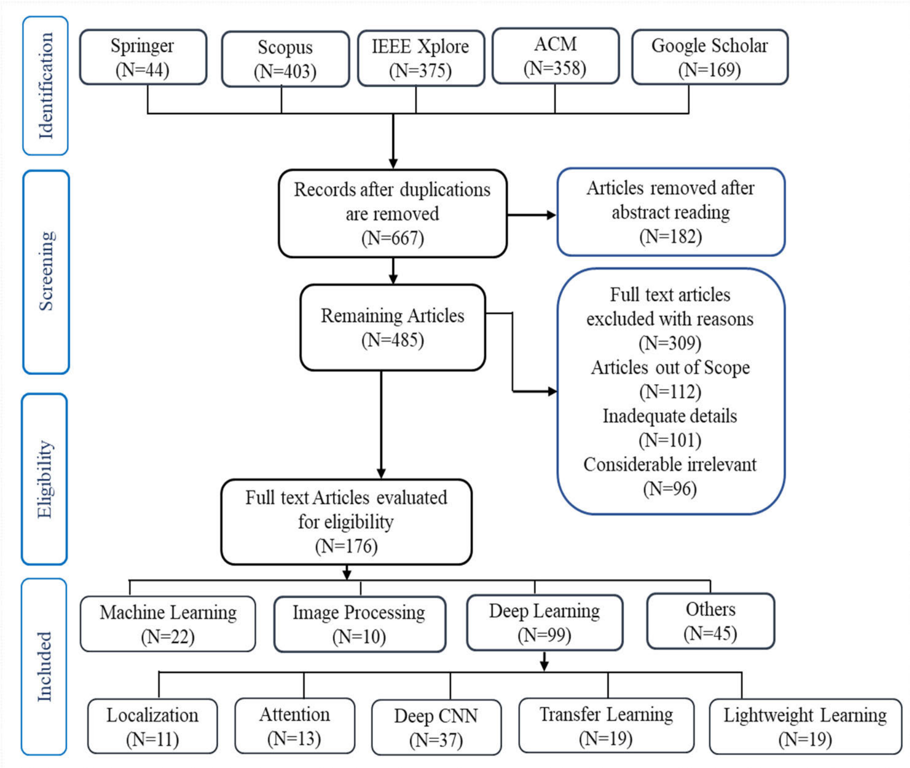



**FIGURE 2.** PRISMA systematic literature review flowchart.

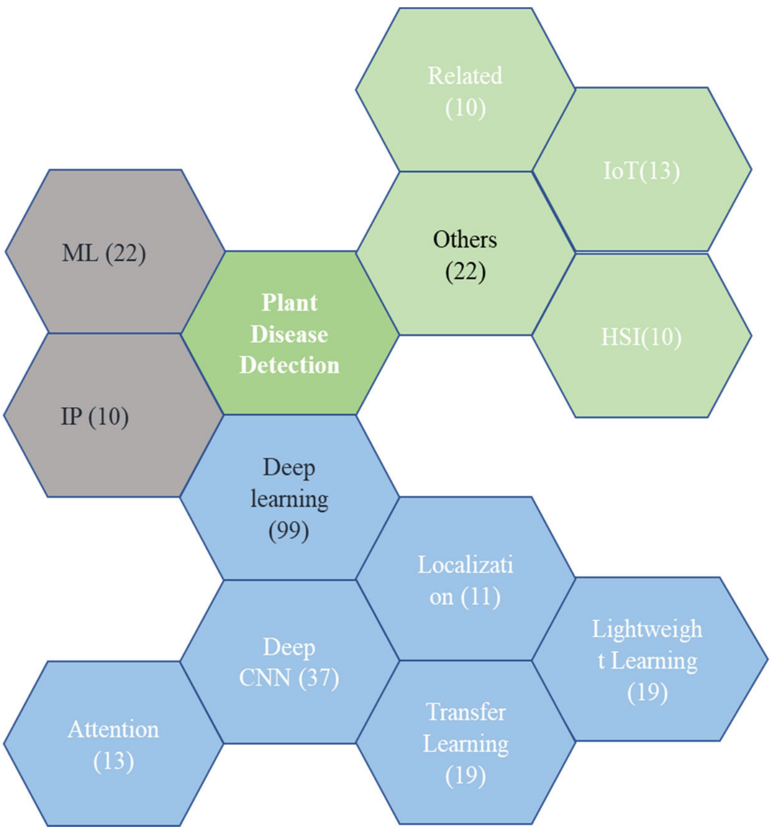



**FIGURE 3.** Utilized in articles with the focus on image processing, deep and machine learning approaches.

examined. The PRISMA was used to screen potential articles and choose those that passed the screening as early as possible [35]. Out of a total of 1349 papers that were obtained from several databases, 169, 364, 357, 403, and 44 articles were obtained from Google Scholar, IEEE Xplore, ACM, Scopus, and Springer, respectively. Once the duplicates were taken out of the list, 579 items were chosen. After reading the abstracts of the papers, the first round of screening resulted in the elimination of 125 of them since they were irrelevant to the study. After reading the articles in their entirety for the first assessment, the second examination focused on determining whether the remaining 454 articles were relevant to the topic. Some other articles were removed because they lacked sufficient information, specifics, and rigor to be considered credible sources. Fig. 2 illustrates the stages of screening and selecting the research that was included in the study.

## V. RESULTS AND DISCUSSION

Within this section, the identified research questions are reacted to by detailing the contributions made by the researchers who contributed to each of the 176 research studies. Also, both quantitative and qualitative assessments of these studies are provided. Fig. 3 below shows the matrices of the used articles within the study.The significance of these methodologies for PDDs was considered in the review.

### A. RESULTS

#### 1) RQ1: WHICH PLANTS AND ARTIFICIAL INTELLIGENCE METHODS ARE THE BEST FOR DISEASE IDENTIFICATION?

A wide diversity of plant species is considered when diagnosing plant diseases in various parts of the world. It is evident that most of the research efforts done in the field of PDD are based mainly in India and China. Plants like apples, soybeans, avocados, bananas, citrus fruits, maize, coffee, millet, cucumbers, grapes, oil palms, potatoes, rice, strawberries, sugar beets, tomatoes, and wheat, among various types of crops, are grown worldwide and are considered for disease detection testing. The results of the PDD tests conducted on frequently grown crops, such as those listed in Table 4, include grapes, rice, apples, cucumbers, maize, tomatoes, wheat, and potatoes. This section also includes a discussion of the ultimate results obtained for each crop type and the vision-based approach utilized to obtain those results. There have been 17 studies on rice that use a variety of IP, ML, and DL techniques. Some of these studies include [35]. By utilizing the mobile network version 2 model with the SE block-based attention approach, the authors reached the most significant accuracy level, which was 99.33%. Furthermore, 11 cucumber studies, like in [36], were examined, employing the classification and regression trees classifier and attaining 98.7% accuracy. Using a sequential CNN technique that included squeeze-and-excitation blocks and CBAM in the shuffle network model, the authors [23] obtained a level of accuracy of 99.14% out of the 11 research studies on grapes. Using a feedback network, an area suggestion network, and the categorization, the study demonstrated the most excellent accuracy among the ten-tomato literature, which was 99.7% [37]. In [38], PDD in corn was discussed by using a modified Alex Network simulation with multi-scale and dilated convolutions and obtained an accuracy of 98.62%. In studies on citrus, the Bagged Tree classifier, which was used in eight different citrus-related research projects, attained the most incredible accuracy of 99.9%. Their study presents a survey of six prior studies on the detection of apple disease [39].

Using the same dataset, the authors applied the DenseNet121 model, which obtained an accuracy of 93.71% [40]. The author in [41] is the only one of the five re- searchers on potato species to attain an accuracy of 99.67% using the support vector machines (SVM) classifier. The highest level of accuracy was obtained by employing a six-layer CNN method for feature extraction with a total accuracy of 97.3%. The data quality impacts the models' performance; therefore, attention enhances the diagnosis of rice and grape diseases. We further subdivide these approaches into two models.

##### a: HYPERSPECTRAL IMAGING

Researchers have utilized many diverse methods for identifying plant diseases in addition to the more common machine learning and CNN-based approaches. A concise discussion of various alternative methods for constructing PDD methods is presented. Hyperspectral imagery aids in plant disease diagnosis and plant stress level estimations. Hyperspectral imaging techniques in the electromagnetic spectrum use a more comprehensive range of wavelengths, including visible and infrared light. The author utilised the SVM and spectral vegetation indices in [20] to predict disease according to the dataset available in 2010 [42]. Their model attained an accuracy of 97% when applied to the dataset consisting of sugar beetroot leaves. The authors utilized KNN and NB classifiers to identify oil palm leaf diseases. On the validation DSS, the proposed method attained an accuracy of 92% [43]. To construct a disease classification model utilizing hyperspectral images, we first performed several image preprocessing approaches, and then we used a super vector machine classifier [44]. The authors [45] used aerial photos obtained via the unmanned aerial vehicle (UAV) with hyperspectral sensors to perform tasks. It was demonstrated that their model has a classification accuracy of 92.50% when applied to the sugarcane datasets. An ensemble technique using hyperspectral images was developed to identify plant diseases and stresses like sand stress [46].

Using the SVM on photos captured in the near-infrared and shortwave infrared, in terms of potato virus Y detection, an accuracy of 89.8% was obtained. A nondestructive remote sensing approach with DT and multilayer perceptron was used to identify avocado tree deficits. For a variety of conditions, the model's accuracy ranged from 82% to 100%. A nondestructive remote sensing approach with multilayer perceptron applying DT was used to identify avocado tree deficits. The Monte Carlo approach is combined with support vector machines (SVM) for disease diagnosis in grapevines. The model had an efficiency that ranged from 66.67% to 89.93% [22], [47], [48], respectively.

### b: VISION-CENTERED SOLUTIONS

RiceTalk is an application that was built after the weather gathering station AgriTalk served as the inspiration [49]. They concentrated their efforts on gathering meteorological data to predict rice blasts. To construct a three-layer CNN model, sensor data was gathered from several different geographic areas. Based on data collected for 14 days, their method reached an accuracy of 89.4%. An advanced process known as airport surface detection equipment utilizing HIT was developed. Their approach demonstrated remarkable performance, with an astounding accuracy of 98.5% in disease categorization [50], [48]. Finally, an IoT-built system for the PDI and pests, in which unmanned aerial vehicle devices gathered photos of farms following a predetermined and preplanned approach, and the recorded images were uploaded to the cloud for plant disease evaluation [22].

An IoT-aided plant disease diagnosis where sensors were utilized to gather plant images and a convolutional neural network was employed for disease assessment [51], an accuracy of 99.2% was obtained using the publicly available PVD. An intelligent agricultural system consists of three layers: perception, edge computing, and data analysis. The authors further compared the various approaches that are accessible, including the problems as- sociated with their dependability and security. The estimate of coffee production was the primary emphasis of their model. XGB model with the highest performance demonstrated that its root-mean-square error value was 0.008, its MAE (loss function) value was 0.032, and its RSE value was 0.585 [52].

IoT-enabled fuzzy network classified the images after extracting the image features using SIFT, optimizing the features with the firefly method, and using SIFT for feature extraction [53]. On a dataset consisting of Alstonia Scholaris trees, their model reaches a uniqueness of 80.66% and a sensitivity of 80.18%, performing the task of disease detection using a simulation of IoT systems. They have demonstrated that their model obtains a maximum accuracy of 91.56% using data from PlantVillage and the trigonometric classification based on neural networks.

An end-to-end approach combines IoTs and DP to diagnose rust illness in pearl millet [54]. They classified the diseases via a 7-layer CNN, utilized the GradCAM model to visualize the characteristics of the features and reported an accuracy of 98.78%. Moreover, authors in [55] produced a prototype for an intelligent agricultural system that uses a mobile application. They gathered data on the soil samples and weather to determine the trends in water consumption. They used XGB, NB, RF, and DT on the dataset that was collected, and they claimed that RF performed the best out of all available options obtaining 91.59% of accuracy.

**TABLE 4. Current plant disease detection models with globally grown plants.**

| Plant and crop types | Current studies | Outstanding Performance |
|---|---|---|
| Wheat | [42], [43] and [44] | Using a six-layer CNN model and decision tree (DT) [42], they obtained 97.3% accuracy. |
| Potato | [45], [46], [47], [48], and [49] | The accuracy of [45] was measured at 99.67% using an SVM classifier. |
| Apple | [50], [51],[52], [53], and [54] | The authors [54] used the DenseNet121 model and were able to attain an accuracy of 93.71%. |
| Citrus | [40], [55] and [56] | Using the bagging tree classifier, [40] was able to obtain 99.9% accuracy. |
| Corn | [20], [57], [58], [59], [60], [39], [61] and [62] | An accuracy of 98.62% was attained by utilizing a modified version of the AlexNet model that included dilated and multi-scale convolutions [39]. |
| Tomato | [63], [64], [65], [66], [67], [38], and [69] | [63] obtained an accuracy rate of 99.7% by utilizing a feedback system and a classification network. |
| Grapes | [36], [27], [71], [72], [73], [74], [75], [76], [77] and [78], [79] | [78] obtained an accuracy of 99.14% using an SCNN model in combination with a ShuffleNet model of CBAM and SE blocks. |
| Cucumbers | [80], [81], [82], [83], [84], [85], [86], [87], [88] | With the help of the CART classifier, [81] obtained 98.7% accuracy. |
| Rice | [89], [90], [57], [91], [92], [93], [94], [95], [96], [97], [98], [99], [100], [101],[102] | The accuracy of [102] was 99.33% utilizing the MobileNet version 2 approach with the SE block-centered attention method. |

### 2) RQ2: HOW DOES THE PRACTICE OF LOCALIZATION CONTRIBUTE TO THE DEVELOPMENT OF REAL-TIME PLANT DISEASE METHODS?

In in-field datasets, image taxonomy is not the only concern; disease localization also falls into that category. The authors in [109] have included a CNN equipped with a CBAM as part of the primary network of the faster RCNN to facilitate the extraction of visual features. Their model achieved an accuracy of classification of 99.95% and a mean average precision of 77.54% on all 3531 photos included in the strawberry dataset's four categories. In [63], we utilized GoogleNet to extract visual features and the SDD structure in localization. On the Apple dataset, their model had a mean accuracy percentage of 78.80%. Reference [73] have used Retinex for fine-tuning, IP, feature extractions, and RPN for detecting and localizing northern maize leaf blight in maize leaves. Their multilevel feature fusion model on the test dataset got an mAP score of 91.83%.

An investigation on using the MobileNetv2-YOLOv3 model in diagnosing the illness known as tomato gray leaf spot They fed the approach with 2385 tomato leaves taken under field conditions and used transfer learning to train the model. Their proposed approach obtained 93.24%, 91.32%, and 86.98% on F1-score, an average accuracy, and an IoU score, respectively [77]. Authors [35] have further used the RPN segment in conjunction with VGG16 and ZFnet. The trained prototype used a wheat data dataset and attained a mAP of 88.9% with the VGG16 model. CNN's model for localizing northern leaf blight using maize leaf photos They created an end-to- point method called Cascaded MRCNN for a segmentation loss function of 2.0437 and measured 91% accuracy [71]. Image classification methods were utilised, including translations, YOLO version 2, and DarkNet-19 approaches. The technique attained 87% canopy mAP data [111]. Using the apple disease dataset, a CNN model for the apple disease localization was proposed and demonstrated a score of 83.12% mAP for the five-class [65]. Using an improved localization SSD method for the plant disease was proposed, and their model presented 92.2% mAP using PVD [112].

Faster RCNN, DetectorRS, CenterNet, CascadeRCNN, FoveaBox, Yolo v4, CenterNet2, and Deformable Detr were also given some fine-tuning. Using the localization dataset on citrus disease, the authors were able to get the greatest mAP possible with CenterNet2, which was 0.914 [68]. There are not many papers in the field of disease localization since there are not many DSS, and the expense of labeling large datasets is costly. Therefore, it is necessary to make more improvements in the field of plant disease localization studies to accomplish accurate disease detection at the field level.

### 3) RQ3: WHAT INFLUENCE DO COGNITIVE CNN MODELS HAVE ON THE DETECTION OF PLANT DISEASES WHEN THEY ARE APPLIED?

CNNs with attention mechanisms are becoming increasingly used in identifying plant diseases. CNNs activate and store beneficial features via the attention mechanism. This speeds up CNN convergence and disease detection. Residual CNN equipped with an attention mechanism for the diagnosis of tomato crop diseases constructed. After being augmented, 95,999 images of tomato foliage were used and attained an accuracy of 98% over ten different classes in the PlantVillage dataset [50]. Moreover, the authors proposed a shallow CNN model that utilized the ShuffleNet model's SE block to implement a CBAM method. The model obtained an accuracy of 99.14% using a dataset of grape leaf images consisting of 4,062 individual images [87]. In [66], image features were extracted using a feature segmentation subnetwork, and feature maps were generated using a spot-aware categorization subnetwork. Both subnetworks were utilized in PDI and PDD. The network was instructed to utilize 404 photos from the Apple dataset, and the scientists found that it had an accuracy of 89.4%. Using a straightforward CNN model, self-attention is represented by residual blocks. Their simulation achieved an accuracy of 98% on the MK-D2 dataset and an accuracy of 95.33% on the AES-CD9214 dataset [113]. Convolution, that is, depth-wise separable and spatial CBAM is available in DenseNet. While the accuracy of the maize in the PlantVillage DSS was stated to be 98.50%, it was proved to be 95.86% in some other maize datasets [56]. Denoising was accomplished by using the binary wavelet transform with Retinex. In addition, the work of background removal was carried out using an implementation of KSW that had been improved using ABCK. RAN was trained to recognize tomato illness by utilizing preprocessed images as training data. Their model scored an 89% accuracy rating in the tests [114]. GAN is equipped with an attention mechanism to produce images and a classification system for plant diseases. An accuracy of 97.9% was achieved during the experiment, which was conducted on a cucumber disease dataset [90].

MobileNet's CBAM and spatial features were incorporated, and the program recorded an accuracy of 99.67% on the PVD. However, on the rice dataset, MobileNet showed just 98.48% accuracy [69]. In [79], it was suggested to use an attention approach with advanced learning for PDD in environments with complex backgrounds. They reached an accuracy of 98.26% using a combination of the PVD and their original in-field data. The custom and plant village datasets yielded 99.78% and 99.33% accuracy, respectively [115].

A modified version of the Mobilenet v2 that incorporates depth-wise separable convolutions. Within the model, they incorporated both channel and spatial attention and attained an accuracy of 99.71% using PVD and 99.13% on a bespoke (for example, paddy, maize, and cucumber) dataset. Similarly, [108] utilized a MobileNet multi-head self-attention rice disease classification model. Bayesian optimization tuned hyperparameters. The model had 94.65%, 92.6%, 89.6%, and 87.4%on accuracy, precision, F1-score, and recall on 2,370 nutritious rice photos in four classifications. Inception and residual blocks [116] suggested a CNN network. The network used a modified CBAM. Their maize, tomato, and potato dataset models were 99.5% accurate.

### 4) RQ4: WHAT ARE THE MOST IMPORTANT CRITERIA TO CONSIDER WHEN EVALUATING THE EFFECTIVENESS OF DISEASE DETECTION SYSTEMS FOR PLANTS?

Various performance evaluation criteria have been devised to evaluate the effectiveness and efficiency of these reviewed methods and classifications in general. For example, we can often use precision, accuracy, F1-scores, mAP, and recall as evaluation metrics for classification approaches. The engineering and medical research communities widely use these statistical parameters in disease localization techniques. The assessment measures are defined by the terms false negatives (FN), true negatives (TN), true positives (TP), and false positives (FP), as defined and expressed below.

#### *a: ACCURACY*

The term "accuracy" is the proportion of correct predictions made compared to the total number of data points collected (T). In scientific literature, it is referred to as recognition, correctness, or success rate.

$$\text{Accuracy} = (\text{TN} + \text{TP})/\text{T} \quad (1)$$

*b: PRECISION*

Precision is described as the proportion of actual positive samples found to the total samples anticipated to be positive.

$$\text{Precision} = \text{TP}/(\text{TP} + \text{FP}) \quad (2)$$

*c: RECALL AND SENSITIVITY*

The term ''sensitivity'' or ''recall'' refers to the proportion of correctly anticipated positives to the total number of actual positive results.

$$\text{Recall} = \text{TP}/(\text{FN} + \text{TP}) \quad (3)$$

*d: F1-SCORE*

The F1-score is a definition that refers to the harmonic mean of both precision and sensitivity (recall).

$$\text{F1} = 2 * (\text{Recall} * \text{Precision}) / (\text{Recall} + \text{Precision}) \quad (4)$$

*e: SPECIFICITY (SPE)*

This is the ratio of precisely anticipated negatives relative to the total number of observed negatives.

$$\text{Specificity} = \text{TN}/ (\text{FP} + \text{TN}) \quad (5)$$

*f: mAP*

The area beneath the precision and recall curve can be considered the standard for precision (AP). A batch of n samples is used to calculate the mAP, which is the same thing as the mean of the median precision values $\text{AP}_\text{i}$, i = 1, n samples. Table 5 presents the attention mechanism PlantVillage dataset studies.

$$1/n \sum \_(i = 1)\hat{\ } nAPi \quad (6)$$

5) RQ5: WHAT KIND OF IMPACT DO LIGHTWEIGHT CNNS HAVE ON THE PROCESS OF IDENTIFYING PLANT DISEASES OR DETECTING THEM?

In recent years, SCNN approaches have become increasingly popular as practical classifications in PDD. There has been a provision on performance with the most advanced deep CNNs on several different datasets. A unique CNN method consisting of pooling layers stochastically and five convolutional layers exhibited an accuracy of 95.48% after being applied to 500 photos of rice illness organized into ten categories [92]. In [123] and [124], they built a CNN model that consisted of only three convolution layers and claimed an accuracy of 93.4% on the cucumber dataset. A tiny CNN model with six layers described a classification precision of 96.46% on 39 different classes after applying various data augmentation techniques [125]. Image backdrop by putting them into a ten-layer CNN for soybean crop disease categorization. The accuracy of their model was determined to be 98.14% [126]. Applying a fundamental eight-layered CNN model, the authors [128] demonstrated a diagnostic accuracy of 98.4% for tomato diseases using the PVD.

Image feature extraction was performed using a shallow five-layer CNN model by the authors [90], who then moved on to a 10-layer CNN model. Fold-based cross-validation support for SVM classification Moreover, in [68], the tomato varieties were used while removing the background. Their model has an accuracy of 98.6% across ten different classes. In [39], enhanced the images using a piecewise log transform, an improved Retinex method, and wavelet basis function image enhancement before feeding the images to a CNN model. Moreover, it employed wavelet-based image enhancement. A PRelu activation function was utilized in their modified version of the AlexNet model, which had dilated and multiscale convolutions. The proposed model achieved 98.62% accuracy, and [128] further used the SE inception module, batch normalization layer, and multiscale feature extraction method in CNN (FLOPs). In [75], researchers extracted features from the first two VGG16 blocks to minimize the model size. SVM and random forest methods are classified. Their approach was tested on maize, apple, and grape plant images from the PlantVillage collection, and a little model showed 93% accuracy. A classification model that was a modified version of DenseNet. The trained corn model of 12,332 images divided into four groups and achieving an accuracy of 98.06% by utilizing the Adam optimizer was presented [62]. A variance of plant symptoms and diseases as a time function developed a CNN model that could capture variations. The process of developing their categorization model consisted of two parts. In the process's initial step, a rice dataset was obtained and then partitioned into several classes because of the intraclass variance. During the second step, the study investigated both fine-tuning and transfer learning (TL) as potential solutions, and their model attained an accuracy of 93.3% [95].

With a total of 841 grapevine infield images across three different categories, the highest accuracy reported was 94% after HSV and improved CNN [70] on three distinct CNN models for the diagnosis of the severity of the Vigna mungo virus for VirLeafNets. They reported an accuracy of 91.23%, 96.42%, and 97.40% [102] using photos gathered from unmanned aerial vehicles. Wheat diseases were identified using a dual wheat disease identification method based on DTs and CNN models, and it achieved an accurate diagnosis rate of 97.3% [42]. Also, the [32] model attained an accuracy of between 90.6% and 97.9% for estimating the severity of the condition and classifying it [130], respectively. A CNN model with seven layers was created by [36] for classifying and segmenting diseases. On grape photos taken from the PVD, the model obtained an accuracy of 91.62%; on 500 leaf images, it produced an accuracy of 93.75%. Researchers in [89] proposed a basic two-layer CNN for visual feature extraction using feature selection and a fish swarm optimizer. The classification was done using ANN, SVM, and LSTM techniques. On a total of 4,800 photos

**TABLE 5.** Summary of the studies using attention on CNN for plant disease identification.

| Method | Capturing Condition | Dataset(s) | Performance (%) | | | | | Reference |
|---|---|---|---|---|---|---|---|---|
| | | | Accuracy | Precision | Recall | F-1 | Others | |
| modified CBAM, residual, inception | Laboratory | 38,466 images of tomato, potato, and corn of seventeen categories PlantVillage. | 99.55 | – | – | – | Loss 0.0175 | [121] |
| Bayesian optimization, self-attention, MobileNet | Laboratory | 2370 rice leaf images in four classes | 94.65 | 92.6 | 87.4 | 89.6 | – | [100] |
| Channel and spatial attention module, MobileNet v2, Depthwise separable convolution | In-field | 405 images in 20 classes | 99.13 | – | 91.37 | 91.37 | – | [120] |
| SE, MobileNet | In-field | 444 images in 25 classes obtained from Rice dataset | 99.33 | – | 87.87 | – | SPE 99.67 | [102] |
| | Laboratory | 1645 images in 11 classes from PVD | 99.78 | – | 98.83 | – | SPE 99.88 | |
| RAN, Retinex and KSW optimized by Binary Wavelet Transform and ABCK | In-field | 8616 photos of tomato leaves organized into five classes | 89 | – | – | – | – | [70] |
| Attention Mechanism, MobileNet-V2 | In-field | 1107 rice leaf pictures in 12 classes | 98.48 | 90.56 | 90.56 | 90.56 | SPE 99.17 | [57] |
| Depth wise separable convolution, Attention module, Mobile-DANet, DenseNet, transition layer | | eight classes of 133 maize leaf pictures | 95.86 | 83.45 | 83.45 | 83.45 | SPE 97.63 | [122] |
| Self-attention CNN | In-field | 9214 leaf images in 6 classes from AES-CD9214 | 95.33 | – | – | – | – | [117] |

of rice leaves, 97.5% was attained. It has been discovered that CNNs are used with highly restricted datasets or for only one species at a time. Table 6 provides a synopsis of several lightweight CNN models that were investigated in this work.

#### 6) RQ6: HOW EFFECTIVE HAVE THE TECHNIQUES BASED ON TRANSFER LEARNING BEEN IN THE IDENTIFICATION OF DISEASE?

Initially, the author [15] conducted a groundbreaking study using GoogleNet and AlexNet to construct a PDD model

**TABLE 6.** The lightweight CNN overview of crop disease detection.

| Method | Capturing Condition | Dataset(s) | Performance (%) | | | | | Reference |
|---|---|---|---|---|---|---|---|---|
| | | | Accuracy | Precision | Recall | F1 | Others | |
| SVM, 5 layers CNN | In-field | 8,911 rice leaf images in five classes | 96.82 | – | – | – | – | [90] |
| multi size convolutional and Six-layer CNN with channel shuffle models | In-field | 54,305 images in 38 classes from PVD | 97.9 | – | – | – | – | [130] |
| 8-layer CNN | In-field | 1,426 rice leaf images in nine classes | 94.33 | – | – | – | Parameters 0.8M | [95] |
| 11-layer CNN | Laboratory | 12,332 corn leaf pictures in four classes | 98.06 | 98 | 98 | 98 | Parameters 77,612 | [62] |
| 8-layers CNN | Laboratory | Ten classes of 1400 leaf images | 98.4 | – | – | – | – | [127] |
| 10-layers CNN | In-field | 841 grapevine leaf pictures in three classes | 94 | 94 | 94 | 94 | – | [70] |
| 9-layers CNN | Laboratory | The PDDB database has 17,240 photos in 16 classes | 98.14 | 97 | 97 | 97 | – | [126] |
| 5-layers CNN | Laboratory | 39 classes of 61,486 augmented PVD images | 96.46 | 96.47 | 99.89 | 98.15 | – | [125] |
| MobileNet, Depth wise separable convolution | Laboratory and In-field | 82,161 pictures in 55 classes | 98.34 | – | – | – | – | [124] |
| 5-layer CNN | Laboratory and In-field | 14,208 cucumber leaf pictures four classes | 93.4 | 92.18 | 92.1 | 91.98 | – | [125] |
| five-layers CNN | In-field | 500 rice leaf photographs in ten classes | 95.48 | – | – | – | – | [91] |

using their plant disease dataset, which included 54,305 photos divided into 38 categories. In addition to using TL, a remarkable accuracy of 99.35% was attained by the GoogleNet model using the TF technique. The number of photos in the PVD increased to 87,848 over 58 categories. Therefore, various studies have used this improved dataset while developing the plant disease classification model. The study [131] evaluated different neural networks with the highest accuracy on the enlarged plant village dataset [132]. The quantity of the dataset as well as its variety influenced the identification of plant diseases. They used TL on the GoogleNet method using photos that had both the laboratory and the backdrop removed [133]. They removed the background from 1383 photographs in 56 different classes and reached the greatest accuracy possible of 87%. Authors in [135] used the VGG16 model to detect diseases in millet crops and reported a 95%, 90.5%, 94.5%, and 91.75% on accuracy, precision, recall, and F1-score, respectively, using the VGG16 model. Fine-tuning was done on Inception v4, ResNet, and VGG16, among others, using the PVD, which

**TABLE 7.** Study overview on plant disease detection using transfer learning.

| Method | Capturing Condition | Dataset(s) | Performance (%) Accuracy | Precision | Recall | F1 | Others | Reference |
|---|---|---|---|---|---|---|---|---|
| ResNet50, DeepLabV3+ | In-field | 500 grape leaf images | 97.75 | – | – | – | – | [71] |
| ResNet50, and DenseNet121, DoubleGA, DenseNet121, WGAN, VGG16, | Laboratory | 31,361 leaf images from PlantVillage dataset | 99.53 | – | – | – | – | [36] |
| 10 classes from PlantVillage dataset with 20,012 tomato leaf images | Laboratory | DenseNet121, Conditional GAN | 97.11 | 97 | 97 | 97 | – | [63] |
| VGG19, VGG16, ResNet50 and MobileNet | Laboratory | Augmented PVD 3008 potato leaf images | – | – | – | – | – | [46] |
| VGG16 | | | 97.89 | 97.21 | 96.13 | 96.17 | Loss 0.0563 | |
| Inception v3 | In-field | Augmented 65,184 peanut leaf images in four classes | – | – | 77 | – | AUC 0.97 | [141] |
| MobileNet Classification, VGG16, watershed segmentation, K-means clustering segmentation, NASNetMobile, VGG19, Inception v3 | In-field | 1564 coconut stem and leaf pictures in four classes | 85.23 | – | – | – | – | [140] |
| EfficientNet B4 | Laboratory | Augmented PVD 61,486 leaf pictures 39 classes | 99.97 | 99.39 | 99.38 | – | Specificity 99.98 | [139] |
| ResNet50, Inception v3 AlexNet, VGG16, EfficientNet | | | – | – | – | – | – | |
| Xception, MobileNet v3, ResNet18, AlexNet, | Laboratory | 109,290 tomato augmented PVD leaf pictures in 10 classes | 98 | – | – | – | – | [64] |
| MobileNet v2, v3, NasNet | | | | | | | | |
| Inception v3, DCGAN | Laboratory | 5406 citrus leaf pictures from PVD | 92.60 | – | – | – | – | [142] |
| ResNet | In-field | 24,144 and 5941 leaf images in 17, and 24 classes from PVD, respectively | 91.2 | – | – | – | – | [138] |
| ResNet | Laboratory | | 94.7 | – | – | – | – | |
| VGG16, VGG19, LeNet, AlexNet and ResNets | – | – | – | – | – | – | – | |

**TABLE 7.** ***(Continued.)*** **Study overview on plant disease detection using transfer learning.**

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| MobileNet, Image segmentation, ShuffleNet, DenseNet, GrabCut algorithm, Inception | Laboratory and In-field | 38,072 leaf pictures in twenty-two classes | 91 | – | – | – | – | [137] |
| Inception v3 (48 layers) and VGG16, GoogLeNetBN (34 layers) | Laboratory | 54,305 leaf pictures in 38 classes | 98.61 | – | – | – | – | [138] |
| | In-field | Bing dataset | 26.92 | – | – | – | – | |
| | Laboratory | IPM dataset | 45.95 | – | – | – | – | |
| EfficientNet | In-field | Augmented 20,256 cucumber leaf images in 4 classes | – | – | – | – | – | [87] |
| EfficientNet-B4 | | | 97 | – | – | – | – | |
| Focal loss | Laboratory | 2462 apple leaf images in six classes | 93.71 | – | – | – | – | [41] |
| Multi-label classification | | | 93.31 | – | – | – | – | |
| Regression | | | 93.51 | – | – | – | – | |
| DenseNet121 | | | – | – | – | – | – | |
| ResNet, VGG16, Inception v4, DenseNets with 121 layers | Laboratory | PVD 54,305 leaf images in 38 classes | – | – | – | – | – | [18] |
| DenseNet121 | | | 99.75 | – | – | – | Loss 0.0159 | |
| VGG16 | In-field | 711 pearl millet leaf images in two classes | 95 | 90.5 | 94.5 | 91.75 | F-Measure 91.67 | [134] |
| GoogleNet | Laboratory | 1383 images in 56 classes | 87 | – | – | – | – | [133] |
| VGG | Laboratory and In-field | An extended PVD 87,848 leaf pictures in 58 classes | 99.53 | – | – | – | – | [131] |
| VGG, AlexNet, Overfeat, GoogLeNet | | | – | – | – | – | Error 0.0223 | |
| GoogleNet and AlexNet | Laboratory | PVD 54,305 leaf pictures in 38 classes | 99.35 | 99.35 | 99.35 | 99.34 | – | [15] |

has 54,305 images. According to their research findings, the DenseNet121 model had the best accuracy, coming in at 99.75% [135]. In a separate piece of research referred to as [12], the authors employed DenseNet models on multilabel classification and regression with focal loss to identify plant diseases and achieved an accuracy of 93.51%, 93.31%, and 93.71%, respectively. These results were based on the classification of the images using the DenseNet121 model [41]. Another study focused on collecting photographs of cucumber leaves from a greenhouse for disease diagnosis [12]. They analyzed the results obtained from utilizing several EfficientNet models and compared their effectiveness. Over 38,072 images, the EfficientNet-B4 technique attained 97.5% accuracy. For disease identification, we gathered greenhouse cucumber leaf images [87]. EfficientNet scored 97.5% on 38,072 images after augmentation. In another study [136], GoogleNet scored 44.54% using the IPM dataset, 28.13% using the Bing dataset, and F1 scores of 99.35% using the PVD. Also, utilization of the GrabCut technique for image segmentation was proposed and trained on the 38,072 images from PVD, and their in-field dataset achieved an accuracy of more than 80% [137]. With varied preprocessing processes in each study, distinct models outperform one another. TL models are presented in Table 7. It is observed that in most instances, the VGG16 model proved to be the most effective.

ResNet is the highest-performing model for plant disease identification out of VGG19, ResNets, LeNet, VGG16, and AlexNet. It achieved 91.2% accuracy when tested on

5941 images of leaf samples from 24 separate classes taken in the field [138] and employed DCGAN to produce synthetic images to enhance the size of the dataset. They evaluated the Inception v3 method's performance after adding more data on citrus trees from the PVD and comparing the results. The model's accuracy was 92.60 percent, which was 20 percent higher than it would have been without such data augmentation [117]. The effectiveness of MobileNet V2 and V3, Xception, and NasNet Mobile on PVD entailing 109,290 tomato leaf pictures for real-time disease diagnosis [64].

Assessment of the accuracy of five diverse neural networks methods like EfficientNet, Inception v3, AlexNet, ResNet50, and VGG16 on 61,486 photos from 39 different classes in the PVD after the dataset was augmented reported a 99.97% accuracy [139]. The effectiveness of several current models found that the MobileNet prototype surpassed the competition with an accuracy of 82.1% for categorising the coconut crop disease syndrome [140]. Improved accuracy of spotted wilt virus detection using the Inception v3 standard in peanuts on the validation dataset; they achieved an AUC of 0.97, with a sensitivity of 77% and a specificity of 98% [141]. Similarly, on the same data, the VGG16 approach accomplished the maximum level of accuracy, which was 97.89% [46]. Utilized CGAN for data enhancement on the DenseNet 121 model and a transfer learning technique for classifying plant diseases. The classification accuracy of their model for tomato diseases into five categories, seven categories, and ten categories was 99.51 %, 98.65 %, and 97.11 % [63], respectively. Also, a method known as "DoubleGAN" was devised to produce high-resolution images using two distinct GAN models. The first one was WGAN, which was for maintaining a healthy class image and balance. The next one was a super-resolution GAN to produce images with high resolution. After using the DoubleGAN model, they examined the results of VGG16, ResNet50, and DenseNet121 [142]. Using a subset of the PVD, they found that DenseNet121 had the highest accuracy at 99.53%. However, researchers combined DeepLabV3+ and ResNet50 for plant disease segmentation [71]. They use fuzzy rules to assess disease severity. Their grape leaf model was 97.5% accurate. According to the investigation, various studies have been completed utilizing the fine-tuning and TL of cutting-edge models. They have been applied in the bulk of works utilizing the PVD, VGG, DenseNet, and ResNet Inception prototypes.

#### 7) RQ7: IN WHAT WAYS DO CONVENTIONAL IMAGE PROCESSING AND MACHINE LEARNING APPROACHES ADD TO THE COMPLEXITY OF DETECTING PLANT DISEASES?

Researchers have analyzed the most essential machine learning techniques to enhance disease classification and detection systems. The previous section's criteria were used to choose twenty-seven research publications. CNNs are an integral part of the process by which conventional IP research is advanced. CNNs have been instrumental in the development of a variety of approaches to the diagnosis of plant diseases. CNNs have a wide application range that can be accomplished through either unsupervised or supervised learning. For picture clustering and other applications, unsupervised learning approaches utilize the capability of CNNs to learn feature representations and extract features for further processing. For problems involving classification, the CNN architecture can be employed as a solution that works from beginning to end. In addition to this, it has also been utilized as a feature extractor for solving categorization issues. Other classifiers, including DT, NB, RF, and SVM, are provided with the characteristics that were extracted from the CNN as presented in [42], [49], [99], [144], [145], and [146]. There has been much success in applying the characteristics collected by CNNs to problems involving the categorization of images, the localization of plant diseases, and the segmentation of images. VGG and AlexNet were utilized in addition to parallel feature fusion for feature extraction. A genetic algorithm was used to select features, and then the results were input into an SVM for classification [144]. With a total of 6309 apple leaf and banana leaf photos, the classification accuracy was 98.60%.

Image feature extraction was accomplished by [49] using a convolutional autoencoder. The SVM that was used to diagnose plant diseases received the retrieved features as input. According to their model, training on the 6,004 maize and potato leaf images taken from the PVD achieved 87.01% accuracy. A convolutional neural network (CNN) incorporates multiscale features; after being augmented, their model had a 94.65% success rate when applied to a dataset including 35,000 photos of cucumbers [87]. A method for identifying plant diseases and determining their severity based on the utilization of residual blocks and shuffle units achieved 98% accuracy, as demonstrated in [146]. The model attained an accuracy of 91% when estimating the severity of the condition. Reference [147] used a DCGAN to supplement the data on a dataset, including information about tea leaf diseases. They achieved an accuracy rate of 90% when building the classification model with the help of VGG16 and the tea disease dataset. They have acquired five separate in-field crop datasets with 121,955 images. The model achieved an overall accuracy of 98% when applied to all five crop datasets, as detailed in [17]. With the model-based simulator, they got a score of 64.3% in terms of segmentation using the SegNet-based approach [50]. Probabilistic programming with Bayesian deep learning and fine-tuned VGG16 model achieved an accuracy of 96% using PVD 54,306 images [60]. On the Kaggle dataset of 15,408 maize species pictures, the model had 98.2% accuracy [58]. Authors in [36] merged the VGG-16 pretrained Inception v3 and ImageNet weights with a random weight initialization into a single algorithm. Their models were 84.25%, 92%, and 80.38% accurate on the maize PVD, rice dataset, and bespoke maize dataset. Authors [98] gathered 5,932 in-field rice images divided into four categories and evaluated the effectiveness of eleven CNNs based on transfer learning in addition to an SVM classifier using the data, achieving an accuracy of 98.38%.

In [94], the AlexNet model extracted features of rice diseased; the model was trained on 60,000 rice leaf photographs and had an accuracy of 96.8%. Self-supervised tomato plant disease detection in a location network, including feedback, region recommendation, classification, and networks. Localization networks employed user-defined loss functions. They trained the model with 16,470 PlantVillage images, added data, and balanced classes. The dataset was 99.7% accurate [38]. Asymptotic non-local denoising was followed by parallel convolution with filters of various sizes. The CNN model replaced the Softmax layer with an upgraded PSO extreme learning machine. After augmentation, 102,052 peach images had an accuracy percentage of 88.13% [18]. They have created a hybrid model that combines the ReseNet 50 and Inception v3 datasets. The accuracy of their model was the greatest possible, coming in at 98.57% for grape disease categorization. Employing a UAV device, we were able to acquire a dataset for the categorization of Pinus tree disease [72]. The AdaBoost classifier was then fed the extracted features to make its determination. Their model performed exceptionally well on the dataset, with 78.6%, 95.7%, and 86.3% on precision, recall, and F1-score, accordingly [147]. Studies like [149] focused on developing a method called FSL to diagnose plant diseases. On the PVD, they utilized the Inception v3 method on the Siamese network splitting the dataset into halves, with each section containing either 32 or 6 classes. They were corrected 91.4% of the time out of 32 classes and 94% of the time in six of the classes. Citrus disease diagnosis was accomplished by [41] using FSL in conjunction with zero-shot learning and a conditional variational autoencoder. It was demonstrated that their model could achieve 53.4% harmonic mean accuracy with zero-shot learning. The green channel of visible-range and infrared pictures has been used by [72] to detect diseases that damage grapevines with an accuracy of 95.02%.

Furthermore, [66] and [67] implement a degressive technique for the generator component and dense connectivity of instances. Grape leaves, totaling 4,062, were used throughout the training process of the network, which also resulted in the generation of synthetic data. The highest possible score that their model could attain was 98.7%. For example, [149] built a CNN model that diagnosed peach disease with 98.75% accuracy using the PVD. Reference [69] introduced DenseNet and reconstructed the residual network. This approach used leaky ReLU-activated tensor-based convolutional layers. The 2018 AI Challenger dataset showed 95% model accuracy. Reference [99] suggested diagnosing plant diseases with a thick block-based CNN model. They merged PlantVillage and the iBean Leaf Image Collection, demonstrating 99.19% accuracy.

Cross-iterative k-means clustering resulted in the developing a clustering model [150]. Image similarity was assessed using siamese networks. Three sets of data were used to evaluate the process. The accuracy of their model varied between 89.5%, 84.9%, and 52.1% among three distinct PlantVillage and Citrus databases. CNNs that use VGG16, Inception v3, and ResNet101 are 5-time trilinear and bilinear. Their model predicted PlantVillage at 99.7% and PlantDoc at 75.58%. Reference [83] tested SqueezeNet-MOD2, AlexNet, GoogLeNet, SqueezeNet-MOD1, SqueezeNet and ResNet50 on the strawberry dataset. ResNet50 had the highest accuracy, at 98.11%. In [145], a comparison was made between machine and deep learning techniques for citrus disease detection into five different classes, as early work showed in [83], [145], [151], and [154]. These models were: ResNet18, ResNet50, ResNet101, and DenseNet201. On the Turkey-PlantDataset, which consists of 4447 images divided into 15 categories, their model achieved an accuracy of 97.56% and 96.83% when employing the ensemble and while utilizing early fusion.

For wheat disease identification, [152] developed a 24-layer CNN model. The accuracy of their model was measured at 97.88% when it was applied to the LWDCD2020 dataset. [153] With the increased amount of in-field backdrop, the CNN model trained with ResNet50 achieved an accuracy of 98.50% on the PVD and 72.03% on the collected field dataset, respectively. VGG16 was used for the multiclass SVM and extraction of image features [154]. The accuracy of their model was measured at 91.3% across the eggplant dataset for all five classes [155]. The model attained an accuracy of 91.19% when applied to the 87,867 photos that were included in the PVD.

Cucumber, Corn, and others developed a spatially pyramid-oriented CNN method for disease diagnosis [156]. Their model had a higher than 90% accuracy rate. Combining DeepLabV3+ and U-Net, researchers [82] developed an innovative CNN model for segmenting plant disease. The study further used DeepLabV3+ to generate segmented images, while U-Net was used to estimate the disease patch coverage. Their model has an accuracy of 93.27% for leaf segmentation, 92.85% for disease severity classification, and a dice coefficient of 0.6914 for detecting and categorizing cucumber leaf diseases. Reference [79] have used GAN for something other than its intended purpose. Using a GAN developed for image super-resolution brings accuracy to 92.16 %. CNN-based PDD models take their influence mostly from industry-standard neural network designs, for example, VGG, Inception, AlexNet, ResNet, and MobileNet, according to an assessment of published research. After undertaking a review of the relevant published research, this was discovered. In addition, many models have integrated CNNs with IP-based image preprocessing techniques [159]. While creating their CNN-based models, several researchers contributed to developing new datasets for the detection of plant diseases. In the study [78], the use of leaf images as a diagnostic tool for disease in grapefruit was suggested. Using the hyperspectral imagery (HSI) color model and an astute edge detector improved the image's textural characteristics. HSI is an abbreviation for the HSI color model. In addition, the color co-occurrence method was employed in conjunction with SGDMs to determine the texture characteristics. They photographed grapefruit leaves in the laboratory and classified them into oily patches, scabs, and regular citrus leaves. Each category comprised forty photographs. According to the presented findings, the accuracy of their models ranged between 95.8% and 100%. Fig. 4 depicts a block diagram of the various processes that are performed by a typical machine learning-based disease detection system, including data acquisition, annotation, processing, feature extraction, and then classification.

Authors in [160] used 117 cotton crop images grown in laboratory settings; the box-counting approach of fractal dimension was used for feature assessment, and SVM was utilized as a classifier. It was demonstrated that a maximum of 94.21% accuracy could be achieved in classification. Using Fermi energy-based region extraction, [94] identified a rice pathogen. A rule-based classifier recognized characteristics chosen using rough set theory (RST). After analyzing 500 rice pictures in four classes from the lab and the field, the accuracy of their model was 94.21%. Regional image descriptors enabled researchers to diagnose a soybean disease with a CCR of 99.83% [163]. A color histogram and a pairwise classification technique were employed for illness diagnosis [32]. During the segmentation of images, they employed a GAC technique, using 1335 images shot in the field; their model attained an accuracy of 58% and a recognition rate of 91.63 %when it came to identifying cucumber disease. In [37], we employed the full color feature on 93 images of cucumber downy mildew captured in the field, and their approach of image segmentation utilizing morphological processes obtained 97.29 percent accuracy. Using the color constancy method and SLIC, [44] aided with the wheat disease categorization research by finding hotspots on the plant's leaves. On a total of 3,637 field images, they achieved 70–85% accuracy. IP stages that have been smoothed, enhanced, denoised, and aligned. K-means clustering of L*A*b color space images with segmentation FFT and log-frequency histogram features is combined. PCA and the sparse representation decision rule were used for feature reduction and classification [84]. They identified 85.70% of 420 images of cucumber leaf disease. Using PSO and association rule mining, [97] developed rule-based incremental classifications. Decision tree (DT) classifiers, Bagged Tree, KNN, Boosted Tree, and Cubic SVM classified gathered features. Their bagged tree-based ensemble model had 99.9% accuracy on 199 controlled citrus leaf pictures split into four groups.

PCA reduced features, and SVM classified cucumber disease using SLIC, EM algorithm, and PHOG. Their model used in-field photographs to have the highest cucumber disease identification rate of 65.41% [87]. The image background was removed from the maximum correlation coefficient and global thresholding based on OTSU [162]. Their model predicts 95% okra YVMV disease and 82.67% bitter gourd disease. Stretching contrast, a top-hat filter, besides the Gaussian function, enhances images. The high-dimensional color transforms saliency strategy includes color, texture, and geometric features. On the 100 features, principal component analysis and support vector machine classification were then performed. Their model has a 95.8% accuracy and 0.98 AUC on 580 field and lab images of citrus [163]. The method demonstrated an accuracy of 89% when tested on 5632 images in four categories from the gathered and PVD. A region-expanding function was employed to extract image data, and bacterial foraging was optimized for the training of CNN. In the hidden layer of the ANN, a radial basis activation function was utilized [164]. Overall, 270 images in the PVD achieved a specificity of 85.58%. Retrieved image features using SPAM and subsequently selected those features using the exponential SMO. In addition to [165] and [166], SVM was employed during the classification procedure. With a total of 1308 photographs obtained in the field from five distinct species of tea plants, the accuracy of their model was 98.5%. Pixels are correlated with EM segmentation [52], optimizers of competitive swarms' selected characteristics. After tenfold cross-validation on PVD 3,171 apple leaf pictures, their model's accuracy was 97.20%. Utilizing Pearson's rank correlations, 15 color characteristics and color spaces were initiated. Photos were identified pixel-by-pixel using classification and regression trees (CART). The proposed detection approach for cucumber disease was 98.7% accurate. GrabCut separates the image foreground from the background using the Gaussian mixture model and Orchard–Bouman clustering. Later, LBP and SVM identified and extracted features 95% of field-grown grapes [123].

Additionally, [168] segmented soybean leaves using k-means clustering to identify leaf diseases. LBP, SURF, and SVM were employed to choose the classification process's features. They have supplied evidence indicating that their algorithm has a 75.8% success rate across 358 images in 8 distinct categories. Both local tri-directional patterns (LTridP) and SVM were used to extract picture features [169]. On a total of 1,882 tomato leaf photos across five different classes from the PVD, their model achieved a 95.7% accuracy rate. Correspondingly, [74] researchers used fractional-order Zernike moments and SVM classifier to identify leaf diseases of grapes and achieved 97.34% accuracy as [79] detected paddy leaf disease and attained 94.25% accuracy. K-means clustering was used to partition the dataset [93]; with the chlorotic and necrotic lesions, an accuracy of 99.67% was obtained. The segmented image was then translated into the domain of the wavelet transform. LBP was generated and then utilized for classification using an ANN classifier on the segmented image. Their strategy achieved a classification accuracy of 95.4% while assessing banana diseases [45] and [169]. Moreover, in [48], authors developed a model for identifying groundnut infections. A Harris corner detector, HOG, and KNN classifier yielded the desired results by correctly detecting infected groundnut with an accuracy of 97.67%. The photographs were modified to use the L, a, and b color spaces. LBP feature extraction was performed on segmented images. ANN, RF, KNN, and SVM classifiers were applied in the classification procedures. Using an SVM classifier on a total of 2840 potato images separated into five

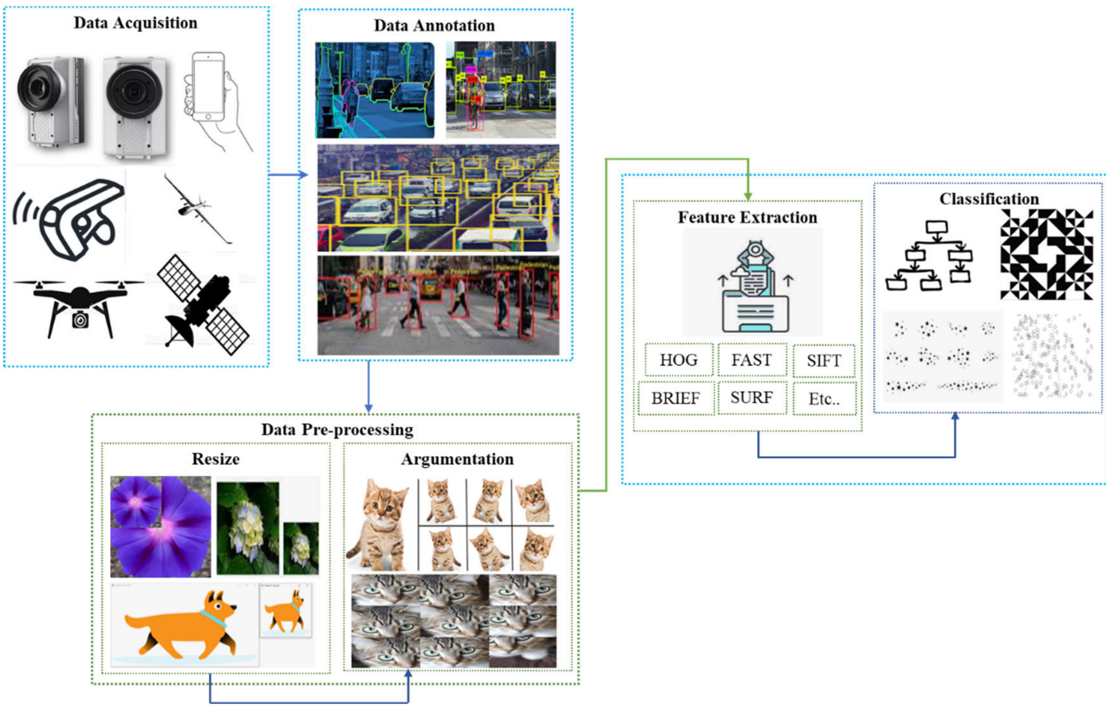



**FIGURE 4.** A simplified conventional machine learning approach.

groups, they achieved a 97.4% accuracy rate, 99.7% on the GrabCut algorithm, and 0.9 IoU on apple leaf images [170] and [171], respectively, on 6980 images.

Most PDD techniques include color modification. Most frequently, these approaches employ LBP and histogram feature extraction algorithms. In extant works, SMO, BoVW, PSO, and PCA are the prevalent feature selection strategies. Some academicians use K-means clustering and SLIC to segment photos pixel-by-pixel. ANN, NB, SVM, and KNN are prominent algorithms for PDI and PDD. Due to PlantVillage's extensive range of plants, most authors have created models utilizing the entire PVD or certain plant species.

#### 8) RQ8: IS THERE AN ADEQUATE PUBLIC DATASET FOR MACHINE AND DEEP LEARNING IN THE PDD AND IDENTIFICATION?

Several scientists have contributed by availing themselves of datasets for a variety of crops. As a result, the public can now access numerous datasets containing information on a broader range of plant diseases and pests (detailed in Fig. 5). Some datasets are generated by capturing images from agricultural farms, while others are compiled in a laboratory with a fixed or eliminated background. In addition, specialized databases are compiled for crop-specific research. These files contain images of a single crop classified into multiple disease groups. These are referred to as single-crop datasets. Other types of databases have an extensive range of crops, and each of these crops has photographs of plants afflicted by a different set of plant or crop diseases. These datasets are referred to as "multi-crop datasets." Finally, this section contains publicly accessible datasets that researchers often utilize. These databases are exploited by researchers in the development of disease detection strategies.

1) PlantVillage: Penn State University introduced this multi-crop dataset widely used for disease categorization. The collection includes 54,305 images of fourteen distinct plant species. These photographs of plant leaves were captured in a controlled setting with a uniform background. The compilation includes data on 38 distinct forms of plant diseases [16].
2) Turkey-PlantDataset: Inonu Universities in Turkey and the Agricultural Faculty of Bingol used a Nikon 7200d camera, the acquire the data for the dataset, which consists of 4447 photos organized into fifteen categories [153].
3) PlantDoc: The collection is compiled from data collected in the field, and it contains 2598 photos organized into seventeen categories [82].
4) PDD271: A massive dataset consisting of 220,592 photos divided into 271 categories. The dataset includes photographs taken in the fields of vegetable, grain, fruit, and tree plants. A Beijing company called Beijing PuhuiSannong Technology Company Limited owns the dataset and has access to a relatively insignificant portion of it [21].
5) LWDCD2020: This dataset has 12,160 images of wheat diseases organized into nine disease classes and one healthy class, all taken under actual field conditions [152].
6) AES-CD9214: The data for this collection was gathered in the field under a variety of conditions, including

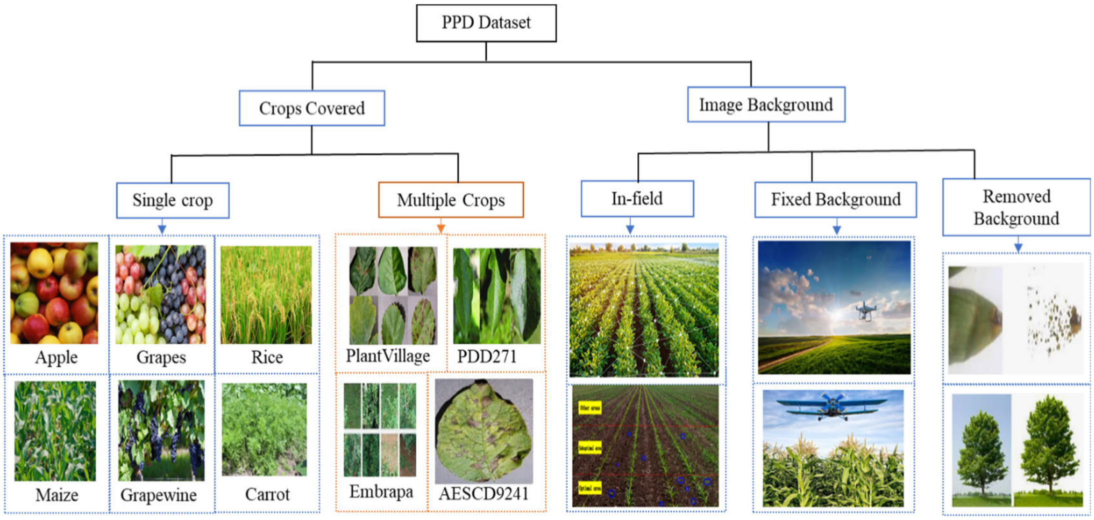



**FIGURE 5.** Dataset types.

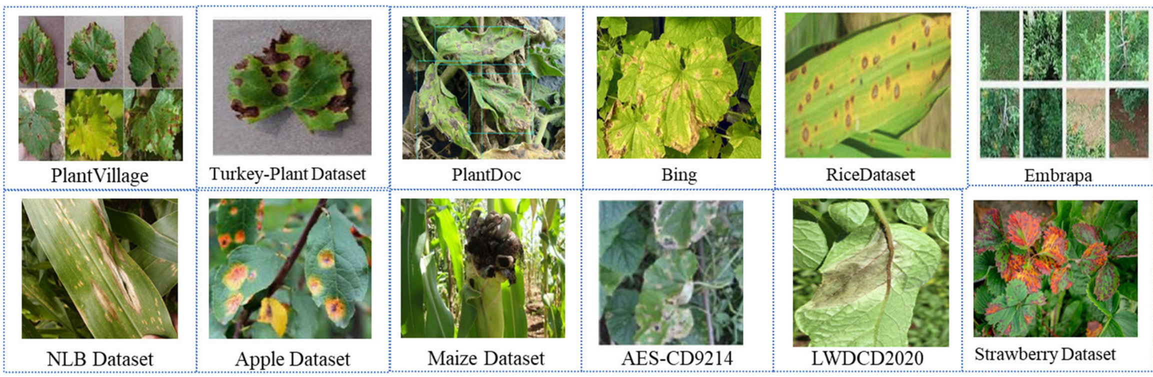



**FIGURE 6.** Sampled example disease images taken each the datasets.

those about angle, resolutions, and illumination. It has 9,214 images, containing 44 different kinds of plant leaf images organized into six categories [117].

7) Rice Dataset: China's Fujian Institute of Subtropical Botany has also made this dataset available to the research community. The collection contains a total of 560 different photos of rice diseases organized into five distinct clusters [119]. It includes photos taken in the laboratory as well as in the field.
8) Maize Dataset: This modest dataset has been made available to the public and was compiled by the institute mentioned above from Xiamen [119]. 481 maize leaf image samples were taken in the field and categorized according to one of four disease classifications.
9) Apple Dataset: A disease identification competition was held on the Kaggle platform before the CVPR 2020 conference. The competition consisted of 3651 photos of apple leaves infected with the disease and fell into one of four categories: healthy leaves despite cedar apple rust, apple scab, and several other disorders [172].
10) NLB dataset: The dataset includes 18,222 photographs of maize taken in the field by UAV-mounted cameras, smartphones, and UAV sensors. There are 105,735 annotations for bounding boxes related to northern leaf blight disease [61].
11) Rice dataset: This is one of the new rice datasets, which contains 1426 photos of different rice classes and images taken in natural field circumstances and provided by the Bangladesh Rice Research Institute [96].
12) Strawberry Dataset: A dataset for the localization of strawberry disease is being compiled, and it has 3,531 photos divided into four types of bounding boxes [114].
13) Embrapa Dataset: The Plant Disease Detection Database (PDDB) was created by the Embrapa Agriculture Institute and comprised 2,326 images of different plant parts that diseases have infected. A subsequent extension of the dataset led to its renaming as the XDB dataset [133]. The XDB dataset contains 46,513 maize leaf pictures, representing 18 species and 93 disease categories.
14) PlantVillage (extended): The initial dataset from PlantVillage was expanded to involve 87,848 photos of 25 plant species, each of which was categorized into 58 disease subtypes [134]. Both in-field and laboratory

**TABLE 8.** Summary of the datasets available (Ref; Reference).

| Dataset | Number of samples | Number of classes | Background of the Image | Accessibility | Ref |
|---|---|---|---|---|---|
| Turkey-PlantDataset | 4,447 | 15 | In-field | Yes | [152] |
| PlantDoc | 2598 | 17 | In-field | Yes | [82] |
| PDD271 | 220,592 | 271 | In-field | | [21] |
| LWDCD2020 | 12,160 | 10 | In-field | Yes | [152] |
| AES-CD9214 | 9,214 | 6 | In-field | No | [117] |
| Rice | 560 | 5 | In-field | No | [95] |
| Maize | 481 | 4 | Laboratory and in-field | No | [119] |
| Apple | 1,821 | 4 | In-field | No | [171] |
| NLB dataset | 105,735 | 1 | In-field | Yes | [61] |
| Rice dataset | 1,426 | 10 | In-field | No | [95] |
| Strawberry Dataset | 3,531 | 4 | In-field | No | [114] |
| XDB | 46,513 | 105 | Laboratory | No | [134] |
| PDDB | 2326 | 171 | Laboratory | No | [137] |
| PlantVillage (extended) | 87,848 | 58 | Laboratory and in-field | Yes | [131] |
| Bing | 121 | 38 | Laboratory and in-field | Yes | [15] |
| IPM | 119 | 38 | Laboratory and in-field | Yes | [16] |
| PlantVillage | 54,305 | 38 | Laboratory | Yes | [15] |

conditions were used to capture the images. However, these are not available to the public any longer.

15) Bing: To evaluate the efficiency of the approaches, [15] downloaded 121 photographs from the Bing search engine. These images had a predetermined background and in-field area.
16) IPM: By compiling this dataset from various Internet sources, [15] has demonstrated the effectiveness of their efforts. The dataset consists of 119 test images, equally distributed between fixed and background conditions. The datasets are listed in Table 8. Fig. 6 displays some example images taken from the database.

### 9) RQ9: ARE RESEARCHERS MODELING PLANT DISEASE DETECTION TECHNIQUES THAT EMPLOY DATA COLLECTION AND PREPROCESSING APPROACHES?

Studies have used digital color cameras to determine the edges of the photos by utilizing a Canny edge detector after converting the images [79]. For data collection [162], we utilized an HP Scanjet 1200 scanner. Reference [32] collected information for the Brazilian Agricultural Research Corporation using mobile cellphones and digital color cameras (Embrapa). Authors [37] captured the data with a Nikon Coolpix S3100 camera while working at the Information Institute of the Tianjin Academy of Agricultural Science. Moreover, they began by converting the photos into HSV color space, then moved on to LAB color space, where they enhanced the colors. To collect what data there was, [44] utilized an iPad, iPhone 5, iPhone 4, and Dell tablet, among others.

The Northwest China Agriculture and Forestry University [84] collected data on cucumbers using a smartphone, a scanner, and a digital camera. For processing, images were transformed into the L-a-b format [15]. Canon EOS 5D Mark III (EF 24–70 mm F2.8L II USM) cameras captured images at a resolution of 5760 by 3840 pixels. Images are then normalized between 0 and 1 after being scaled to 512 by 512 pixels. Image feature extraction was continued with additional applications of the PCA and whitening algorithms [23]. They gathered images for their citrus dataset in the Sargodha area of Pakistan. They used the top-hat filter in conjunction with the Gaussian filter for preprocessing. In another study conducted by [165], a digital single-lens reflex camera was utilized to gather tea leaves. The Anhui Academy of Agricultural Sciences' Agricultural Economics and Information Institute altered the photos so that the color space was LAB for processing [165]. The Agricultural Scientific Innovation Base of the Information Institute of the Tianjin Academy of Agricultural Sciences captured cucumber data using a Nikon Coolpix S3100 digital camera with 2592 by 1944 pixels. Utilizing segmentation to discern between the image's foreground and background [37].

After cutting the images to 240 by 240 pixels, random cropping, rotating, shifting, resizing, horizontal and vertical flipping, and intensity transformation-based data augmentation [147], tea leaves were collected with a DJI Phantom 4 Pro UAV at10 meters using a Canon EOS 80D SLR camera147], tea leaves were collected with a DJI Phantom 4 Pro UAV at 10 meters using a Canon EOS 80D SLR camera. Smartphones were used to collect multi-crop data in Spain and Germany [17]. To capture RGB photos, smartphones and cameras with 1–24 megapixels were utilized. Embrapa, the Brazilian agricultural research corporation, compiled the data.

They inverted the vertical and horizontal orientations to enhance image quality, and rotated, enhanced, and added noise [133]. Table 9 shows the equipment, zones, and preprocessing techniques used for PDD. It was downloaded and classified 124 images of mold diseases. They were improved by zooming, rotating, and flipping [134]. The author in [65] utilized data augmentation techniques such as center zoom, random cropping, zooming, and contrast stretching based on the four classes of tomato species found in the PVD. Only one dataset exists that was obtained using drones; others were obtained using smartphones, digital single-lens reflex cameras, and scanners.

After cutting the images to 240 by 240 pixels, random cropping, rotating, shifting, resizing, horizontal and vertical flipping, and intensity transformation-based data augmentation [147], tea leaves were collected with a DJI Phantom 4 Pro

**TABLE 9.** Data sites, device(s), and preprocessing methods.

| Data collection areas | Device(s) | Preprocessing Approach | Reference |
|---|---|---|---|
| Conghua District, China | Digital cameras | - | [56] |
| Northwest A&F University | BM/BB 500 digital cameras | – | [53] |
| Xiaotangshan National Precision Agriculture Demonstration Base | Digital camera | Augmenting data and resizing | [69] |
| Pakistan | Mobile | Resize, noise removal, and data augmentation | [42] |
| Uttar Pradesh, India | IXUS 285 HS | Data resizing, augmentation, segmentation | [99] |
| Spain | EOS 5D Mark IV | Grabcut Segmenting and background removing | [70] |
| Florida Research and Education Center | Sony a6000 cameras and Piksi multi RTK-GPS kit | Data augmentation | [141] |
| Chennai, India | Digital SLR camera | Data resizing and augmentation | [140] |
| Xiaotangshan National Precision Agriculture Research Demonstration Base | Smartphone | Data Augmenting | [82] |
| Zhengzhou City, China | Cannon EOS 650D digital camera | Resize | [156] |
| Pudukkottai, India | Smartphone | Data augmentation | [154] |
| Inonu Universities and Agriculture in Turkey | Nikon 7200D camera | Resize | [151] |
| Balamore and Millen Farms Limited | Canon DSLR camera | Data augmentations | [157] |
| Muara Wahau, East Borneo, Indonesia | Digital camera in smartphone | $L * a * b$ conversion | [170] |
| United States of America | spectrograph, conveyor belt | - | [27] |
| China | UAV, digital camera, HySpex ODIN-1024 | - | [27] |
| Shandong Province in China | Digital cameras and smartphones | Bounding box labeling | [76] |
| Bangladesh Rice Research Institute | Digital cameras | Data resizing and augmentation | [96] |
| Xinyuan Sunshine Plantation Park | Sony RX100M3 | Resize data and augmentation | [21] |
| Jingyang, Xianyang, China | Digital cameras | Data augmentation | [87] |
| Japan | Digital cameras | Resize and data augmentation | [80] |
| France | MAPIR sensors and Unmanned Ariel Vehicle Quadcopter | Data augmenting | [74] |
| China | UAV | Crop, resize, and data augmentation | [147] |
| Assam Agriculture University, Horticulture Research Station | Smartphones | Data resizing and augmentation | [55] |
| Odisha, India | Nikon DSLR-D5600 | Data augmentation and resizing | [98] |
| Xiamen Institute of Subtropical Botany | – | Data augmentation and resize | [36] |
| Kerala Agricultural University | 24.2-megapixel, CMOS sensor), DSLR camera(Canon EOS 750D) | contrast enhancement and resize | [169] |
| Tamilnadu, India | Digital cameras | Thresholding and HSV based on binary mask invention | [98] |

**TABLE 9.** ***(Continued.)*** **Data sites, device(s), and preprocessing methods.**

| | | | |
|---|---|---|---|
| Northwest A&F University | Digital camera | – | [51] |
| China | Smartphones | Bounding box labeling | [114] |
| INRA Angers greenhouses, France | Digital camera with IR images | Resize | [50] |
| Germany and Spain | Smartphones | Resize, crop, and data augmentation | [17] |
| Tianjingshan National Forest Park, China | UAV DJI phantom 4pro and Canon EOS 80D SLR camera | Data augmentation | [147] |
| Shaanxi, China | A BM/BB-500GE digital color cameras | Data augmentation | [85] |
| Brazilian Agricultural Research Agency | Digital cameras and mobile devices | $L * a * b$ conversion | [167] |
| Tianjin, China | Nikon Coolpix S3100 | Foreground and background pixel segmentation | [37] |
| Anhui Academy of Agricultural Sciences | Digital SLR camera | – | [166] |
| Central Weather Bureau, Taiwan, and Quarantine | barometric pressure sensors, temperature, the relative humidity, and the temperature | – | [88] |
| USA | Spectrometer SVC HR-1024 | – | [143] |
| USA | – | – | [47] |
| University of Manchester, England | whiskbroom sensor, lamps, Monochromatic digital camera | – | [107] |
| Sargodha, Pakistan | – | Gaussian function, top-hat filter | [163] |
| Heilongjiang, China | 5760 x 3840 resolution Canon EOS 5D Mark III | Resize | [23] |
| Hooghly, India | Nikon D5100 | Noise removal, background removal, and the largest connected component | [162] |
| Northwest Agriculture and Forestry University in China | Smart phone, scanner, and digital camera | $L*a*b$ conversion | [84] |
| Spain and Germany | iPhone5, Samsung Galaxy Note, iPad, iPhone4, Dell-tablet, Windows Phone and Samsung S3 | Segmentation, color, and constancy | [44] |
| Tianjin, China | Nikon Coolpix S3100 with maximum pixels of 4320 × 3240 | HSV, L*a*b, excessive index and color enhancement, | [37] |
| Northwest Agriculture and Forestry University | – | Resize | [83] |
| Brazilian Agricultural Research Corporation | Digital cameras and mobile devices | Guided Active Contour (GAC) | [32] |
| UFGD Brazil | 1200 dpi resolution, HP Scanjet 1200, | Resize | [161] |
| Grapefruit Grove, Central Florida | 3 color cameras, with a 28–90 mm zoom lens (JAI MV90), | HSI and Canny edge detector | [78] |

UAV at 10 meters using a Canon EOS 80D SLR camera147], tea leaves were collected with a DJI Phantom 4 Pro UAV at 10 meters using a Canon EOS 80D SLR camera. Smartphones were used to collect multi-crop data in Spain and Germany [17]. To capture RGB photos, smartphones and cameras with 1–24 megapixels were utilized. Embrapa, the Brazilian agricultural research corporation, compiled the data. They inverted the vertical and horizontal orientations to enhance image quality, and rotated, enhanced, and added noise [133]. Table 9 shows the equipment, zones, and preprocessing techniques used for PDD. It was downloaded and classified 124 images of mold diseases. They were improved by zooming, rotating, and flipping [134]. The author in [65] utilized data augmentation techniques such as center zoom, random cropping, zooming, and contrast stretching based on the four classes of tomato species found in the PVD. Only one dataset exists that was obtained using drones; others were obtained using smartphones, digital single-lens reflex cameras, and scanners. CMOS cameras, spectrometers, and lamps collected hyperspectral imaging data. In IoT applications, researchers use sensors to measure temperature, pressure, and humidity. Digital cameras and other sensors may be helpful in disease detection since several factors are involved. Traditional IP and ML plant disease identification systems preprocess data extensively. These methods use human and automatic methods. Still, most DL systems scale, normalize and augment images.

### B. DISCUSSION

This discussion section subdivides the discussion into techniques, data availability, and other general findings.

#### 1) TECHNIQUES

According to this review, deep CNN models dominate PDD compared to localization research. Shallow CNN methods for real-time field applications [173], [174], [175], [176]. Shallow CNN-based models in implementing more innovative IoT-centered agriculture. The current hi-tech deep CNN performs well on well-managed datasets considering early approaches. Due to controlled data collection settings, datasets like Embrapa and PlantVillage provide low-volatility data used to build most models. However, field datasets have not been used much or evaluated during the models' real-time performance. Deep CNN models have a more significant memory requirement than shallow CNN models, which could be a hurdle to their adoption in IoT applications. Nevertheless, external networks are susceptible to minor data limitations. In addition to the required amount of memory, the number of FLOPs should be considered when deciding whether a model is acceptable for IoT deployment. Also, relatively few researchers have examined the models from FLOP's perspective. Sized symptom detection: early plant pathogen is often mild, making identification complex. Thus, early loss reduction requires technologies that can identify even the most minor disease indicators. GAN-based image super-resolution algorithms may potentially help recognize which body sections are affected by the disease at an early stage. Consequently, it is possible to improve the efficacy of illness identification in small populations despite the corresponding increase in the cost of data acquisition.

#### 2) DATA AVAILABILITY

The lack of available in-field datasets is one of the most significant obstacles to consider when developing PDD models that can perform adequately in real-time. Scientific researchers have recently made specific datasets available to the public, although these databases only cover a select few types of crops. In recent years, several researchers have focused their attention, in addition to investigating CNNs' disease detection capabilities, on the mechanisms that control attention. The performance of these models was encouraging; therefore, it is likely that more studies will be conducted in this area. The following is a synopsis of the most significant challenges and potential future areas for research. Close-range data capture: Most publicly accessible datasets were assembled using mobile cameras that captured close-up images. Due to this, the disease-affected portions of the area are typically the most obvious or cover a significant portion of the image. Using these datasets to develop disease detection models for mobile apps or apps with close-range cameras will yield excellent results. However, these datasets may not help locate diseases across a more comprehensive farm or develop UAV-based applications. This is because the disease may appear very small, and drone cameras may not be able to get a clear image of their symptoms. Therefore, not only to gather data from drones but also to make the data public so that methodologies can be created based on these datasets. Diverse and complex background: plant disease detection may be difficult due to lighting, weather, and a changing background in the field. Moving cameras, such as those employed in drone-based monitoring, make it harder to diagnose plants as compared to fixed cameras. This is because the backdrop conditions are constantly present during the training.

Lack of accessibility to standard datasets: It is evident that the original datasets created in the lab were intended for scientific purposes. In the years that followed, academia had access to the same databases, including real-world scenarios. In contrast, practically all infield datasets are created for a single crop. Another issue with our evaluation was that most machines and deep learning models created by academics were based on proprietary datasets or a limited portion of publicly accessible information. Due to this, there was no universally approved mechanism for comparing the effectiveness of distinct approaches, even though they were well-designed for the same plant species. This demonstrates how crucial it is to have benchmark datasets containing real-world scenarios that can be employed to construct models.

Deficiency of datasets for actual application development: Most research uses public datasets, and most are laboratory-generated. In contrast, works that utilize private datasets feature a variety of visual backgrounds. Therefore, it is essential to utilize datasets with field image samples. Although some enormous datasets are available to the public for developing real-world applications, other large datasets are available to the public. As a result, CNN models will benefit from being trained on a greater variety of samples. Adversarial scenarios would be helpful to. The deployment of very complex models in intelligent agriculture solutions involves the fine-tuning of models using field data. Even though highly potent models are readily available. As most in-field datasets are not currently accessible, it is impossible to design reliable plant pathogen and disease classification and detection methods for real-time applications. The creation of increased labeled plant information will improve the development of applications that can capture a broader range of plant species in different parts of the globe.

#### 3) CHALLENGES AND FUTURE TRENDS

According to these reviewed studies, plant pests and diseases have demonstrated huge social, post-harvest, and economic losses in several countries' global agricultural production industries. This is especially true due to climate change's effects over the past several decades. Many practical approaches for detecting, monitoring, and evaluating plant diseases have been continuously researched. These approaches are employed in the fight against plant diseases. In recent years, there has been a shift toward a more significant emphasis on non-invasive technologies. Most implemented models are simulated on small datasets with restricted image backgrounds; therefore, it is vital to use raw images considering the natural setup.

Most of these models use pre-trained CNNs, but their ensemble can improve accuracy in identifying and classifying different plant diseases. The SVM classifier is noted as being among the machine learning classifiers that are mainly used; therefore, testing the suggested models on other classifiers or combining their parameters is a potential trend. Using traditional approaches has been demonstrated that is not ineffective in plant pests and disease classification because of several plant species and disease classification; therefore, using transfer learning will improve model complexity and performance and reduce computation resources. In recent years, one of these technologies, hyperspectral technology, has received considerable interest. Forthcoming systematic or general reviews should scrutinize the works and considerable limitations of innovative agricultural applications, especially on plant pests and detection. Considering sustainable plant pests and disease management incorporates plant disease epidemic insight, healthy agroecosystems will improve and boost plant health and crop quality produce with proper natural resource conservation. Different plant diseases and pests globally affect plant species depending on seasonal and environmental factors making the centralized approach impractical in some countries. Thus, an efficient treatment may be delivered, and large-scale economic losses can be prevented. It is necessary, for example, to establish how to quickly compute the effective area of disease and analyze the severity of infection and insect pests in a region. This is necessary so that adequate treatment may be delivered. These issues remain significant obstacles in plant pest control; other challenges are listed below that must be tackled as soon as practicable.

- Variations in lighting conditions and image quality
- Disease progression stages and inter-class similarity
- Limited availability of diverse and annotated datasets
- Computational challenges in processing large-scale datasets
- Real-time disease detection in the field
- Impact of environmental factors on disease detection accuracy
- Integration of multi-modal data sources
- Development of robust and interpretable models addressing ethical and social considerations
- Climate change effects on plant diseases
- Integration of IoT devices, drones, and mobile applications
- Advancements in data augmentation, transfer learning, and domain adaptation
- Engaging citizen scientists and leveraging crowdsourcing platforms

#### 4) IMPLICATIONS OF THE STUDY

In this section, we briefly demonstrate the implication of plant disease and pests in various ways, as discussed below:

##### *a: IMPACT ON HUMAN*

Plant pests and diseases inhibit water and nutrient absorption, photosynthesis, fruit production, plant healthy growth, and cell division. Depending on pathogen aggressivity, host resistance, environment, duration of infection, and other variables, these diseases may cause moderate symptoms or plant death. Pathogens and contaminated portions can result in leaf spots, fruit spots, root and fruit rots, leaf blights, wilting, and death. For instance, the mild mottle virus interacts with human immune systems and produces clinical signs. Several plant diseases reduce food availability or pollute it with hazardous compounds, causing harm to humans. In addition, humans may be harmed by plant-disease-fighting microorganisms applied to soils like herbicides and insecticides, among others.

##### *b: ENVIRONMENTAL PERSPECTIVES*

Since different plants tend to have several pests and diseases, the traditional farmer opts to apply insecticides and herbicides that lead to land pollution in the long run. Even though most plant pathogens cannot infect people, it is vital to avoid eating moldy or rotten fruits and vegetables from farms where herbicides are used and food tainted with fungi that produce toxins. This is because both food types represent a significant health risk. It is likely that by eliminating infected fruit sections, the amount of pathogen inoculum and decaying fruit can be reduced. However, this does not necessarily suggest that all potential sources of contamination have been eliminated, as certain fungi and toxins can multiply and migrate to areas of natural plant fruit on the farm.

##### *c: ACADEMIA*

Without a doubt, various plant pests and diseases increase different research bases that increase plant disease early identification at the pixel level. This has been tested and found to reduce the chances of using chemicals that raise environmental (see subsection 6.2) and human concerns (see subsection 6.1). As always, there is an urgent need for more study on the direct consequences of plant infections and diseases on humans; however, considerably large plant disease datasets are not available, making the current models practically impossible on small agricultural smart gadgets. Furthermore, mycotoxin-producing fungi and the presence of such fungi in human-ingestible foods necessitate heightened attention and caution. Prioritize food diversification and the development of effective plant disease control systems to avert epidemics of plant diseases like the late blight that afflicted Irish potatoes. This plant disease can be transmitted from one plant to another.

##### *d: GLOBAL FOOD SECURITY*

As explained earlier, plant pests and diseases affect plants directly, but in the long run, they go beyond traditional food shortages to a governmental level, thereby affecting the global food supply caused by pathogens. This is because it varies in genotype, space, and time, making plant administration difficult. Reducing pathogen inoculum, decreasing pathogenicity, and improving crop genetic variety are all methods for combating a disease that requires governments' involvement in research to cater to plant pests and diseases early enough. Plant pests and diseases compromise our food supply; thus, legislators must support their management at all costs.

#### 5) RESEARCH DIRECTIONS
Plant diseases pose significant threats to crop yields and food security worldwide. Detecting and diagnosing plant diseases promptly is crucial to mitigate their impact. In this section, some identified future research directions are presented:

##### *a: INTEGRATION OF MULTI-MODAL DATA SOURCES*
Integrating multi-modal data sources is a promising direction for future research in plant disease detection. This research focuses on several attributes and objectives to effectively leverage the combination of different data modalities. First, diverse data sources like images, environmental data, and genomic information could be identified and gathered to represent plant diseases comprehensively. Robust fusion techniques must be developed to effectively combine information from multiple modalities, considering early, late, or hybrid fusion approaches. Additionally, handling missing or noisy data in multi-modal datasets is crucial for reliable fusion. Assessing the added value of integrating multi-modal data sources compared to using individual modalities is essential in evaluating performance improvements in accuracy, speed, and robustness. Finally, interpreting fused data and understanding the relationships between modalities are important for gaining insights into disease detection.

##### *b: ROBUST AND INTERPRETABLE MODELS*
Developing robust and interpretable models is a crucial direction for plant disease detection and classification. Robust models should exhibit resilience to variations in data quality, lighting conditions, and disease progression stages, while interpretable models provide transparent explanations for their predictions. Achieving robustness involves addressing challenges such as inter-class similarity and variations in environmental factors. Meanwhile, interpretability ensures that farmers and stakeholders understand the reasoning behind disease diagnoses. By focusing on developing robust and interpretable models, researchers can enhance the trust, adoption, and practicality of automated plant disease detection systems.

##### *c: IMPACT OF CLIMATE CHANGE ON PLANT DISEASES*
One aspect of climate change is the alteration of temperature patterns. Rising temperatures can affect the distribution and prevalence of plant pathogens, influencing their survival, reproduction, and virulence. Additionally, changes in rainfall patterns can impact disease spread, as some pathogens thrive in moist conditions. Extreme weather events like droughts or floods can further disrupt plant health and make crops more vulnerable to diseases. Furthermore, shifts in climate can affect the lifecycle of vectors, such as insects, that transmit plant diseases. Climate change can alter the geographic range, intensity, and timing of plant diseases, posing challenges for agriculture and emphasizing the need for adaptive disease management strategies. Understanding these impacts and developing resilient agricultural practices are crucial for mitigating the detrimental effects of climate change on plant health.

##### *d: CITIZEN SCIENCE AND CROWDSOURCING*
Citizen science and crowdsourcing are valuable approaches to plant disease detection. Citizen science involves public participation in data collection while crowdsourcing leverages collective intelligence. These methods offer benefits such as large-scale data collection, collaboration between scientists and communities, and empowering farmers. In addition, they bridge knowledge gaps, provide resources, and contribute to comprehensive disease databases. Citizen science and crowdsourcing revolutionize plant disease detection, monitoring, and management by involving individuals and facilitating timely interventions to safeguard agricultural productivity.

##### *e: SOCIAL AND ETHICAL CONSIDERATIONS*
Social and ethical considerations are vital in developing and implementing plant disease detection technologies. Privacy protection, transparency, and informed consent are essential for data management, and research related to its impact is vital. Balancing intellectual property rights ensures fair access and benefits. Equitable access to resources and technologies should be prioritized for all farmers. Finally, assessing the social and economic impact, particularly on marginalized communities and local economies, is necessary. By addressing these considerations, researchers and policymakers can ensure responsible, inclusive, and sustainable plant disease detection technologies deployment.

## VI. CONCLUSION
In this systematic review, we surveyed studies that present plant disease and pest detection containing IP, ML, DL, and others. It is clearly demonstrated that plant pests and diseases harm the global agricultural industry. Despite the rapid expansion of AI-based solutions, there are still many barriers to overcome before high-performance real-time PDD solutions can be produced, according to a comprehensive assessment of PDD research employing imaging applications. This system review presented a comprehensive overview of current plant pest and disease detection studies. ML, IP, and DL-based plant disease models and monitoring technologies have shown promising results. The study considered 176 articles published between 2012 and 2022. These studies were selected after applying rigorous inclusion criteria from five academic databases, including ACM, Springer, Scopus, IEEE Xplorer, and Google Scholar. Our analysis presented significant relevant findings from the considered studies providing adequate responses to the research review questions. Most studies centered extensively around CNN-based disease detection systems for numerous crops, notably citrus, have been studied. Lightweight and TL algorithms, CNNs, GANs, attention mechanisms, and autoencoders have been investigated for high-functioning model construction, and a more comprehensive range of modifications can still be done in this paradigm to reduce the computation complexity. However, the present training paradigm for DL models requires large

data sets, making finding remedies for many plant diseases difficult. There are a limited number of publicly accessible datasets on this topic. In addition, the bulk of DL models is created using data collected under laboratory circumstances, which may hinder their performance in real-time utilization. This study further resolves that industry and academia have many computation complexities and an excellent opportunity to avail models practically visible for real-field implementation.

Finally, forthcoming reviews should scrutinize the works and considerable limitations of innovative agricultural applications, especially on plant pests and detection, which is another crucial research area. This survey covered a more comprehensive range of plant pests and diseases methods, challenges, and dataset checks and demonstrated that future research sparks new ideas and the concepts of relevant theories, methods, and practices in industries and academia.

## REFERENCES

[1] Q. Dongyu, T. Ghebreyesus, and R. Azevedo, "Mitigating impacts of COVID-19 on food trade and markets," in *Food and Agriculture Organization of the United Nations*. Italy: Press Release, Sep. 2020.
[2] *The Impact of Disasters and Crises on Agriculture and Food Security*, FAO, Rome, Italy, 2018.
[3] *New Standards to Curb the Global Spread of Plant Pests and Diseases*, Web Page of the Food and Agriculture Organization of the United Nations, FAO, Rome, Italy, 2019.
[4] K.-H. Kim, E. Kabir, and S. A. Jahan, "Exposure to pesticides and the associated human health effects," *Sci. Total Environ.*, vol. 575, pp. 525–535, Jan. 2017.
[5] D. Laborde, W. Martin, J. Swinnen, and R. Vos, "COVID-19 risks to global food security," *Science*, vol. 369, no. 6503, pp. 500–502, Jul. 2020.
[6] L. Keeling, H. Tunón, G. O. Antillón, C. Berg, M. Jones, L. Stuardo, J. Swanson, A. Wallenbeck, C. Winckler, and H. Blokhuis, "Animal welfare and the United Nations sustainable development goals," *Frontiers Veterinary Sci.*, vol. 6, p. 336, Jan. 2019.
[7] M. Khan, "Integration of selected novel pesticides with trichogramma chilonis (hymenoptera: Trichogrammatidae) for management of pests in cotton," *J. Agricult. Sci. Technol.*, vol. 21, no. 4, pp. 873–882, 2019.
[8] S. Savary, A. Ficke, J.-N. Aubertot, and C. Hollier, "Crop losses due to diseases and their implications for global food production losses and food security," *Food Secur.*, vol. 4, no. 4, pp. 519–537, Dec. 2012.
[9] F. Ren, W. Liu, and G. Wu, "Feature reuse residual networks for insect pest recognition," *IEEE Access*, vol. 7, pp. 122758–122768, 2019.
[10] E. A. Heinrichs and R. Muniappan, "Integrated pest management for tropical crops: Soyabeans," *CABI Rev.*, vol. 2018, pp. 1–44, Jan. 2018.
[11] M. Margni, D. Rossier, P. Crettaz, and O. Jolliet, "Life cycle impact assessment of pesticides on human health and ecosystems," *Agricult., Ecosyst. Environ.*, vol. 93, nos. 1–3, pp. 379–392, Dec. 2002.
[12] A. Sabarwal, K. Kumar, and R. P. Singh, "Hazardous effects of chemical pesticides on human health–cancer and other associated disorders," *Environ. Toxicol. Pharmacol.*, vol. 63, pp. 103–114, Oct. 2018.
[13] S. Savary, L. Willocquet, S. J. Pethybridge, P. Esker, N. McRoberts, and A. Nelson, "The global burden of pathogens and pests on major food crops," *Nature Ecol. Evol.*, vol. 3, no. 3, pp. 430–439, Feb. 2019.
[14] P. Udmale, I. Pal, S. Szabo, M. Pramanik, and A. Large, "Global food security in the context of COVID-19: A scenario-based exploratory analysis," *Prog. Disaster Sci.*, vol. 7, Oct. 2020, Art. no. 100120.
[15] 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.
[16] D. Shah, V. Trivedi, V. Sheth, A. Shah, and U. Chauhan, "ResTS: Residual deep interpretable architecture for plant disease detection," *Inf. Process. Agricult.*, vol. 9, no. 2, pp. 212–223, Jun. 2022.
[17] 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.
[18] S. Huang, G. Zhou, M. He, A. Chen, W. Zhang, and Y. Hu, "Detection of peach disease image based on asymptotic non-local means and PCNN-IPELM," *IEEE Access*, vol. 8, pp. 136421–136433, 2020.
[19] J. G. A. Barbedo, "Plant disease identification from individual lesions and spots using deep learning," *Biosystems Eng.*, vol. 180, pp. 96–107, Apr. 2019.
[20] J. Chen, J. Chen, D. Zhang, Y. Sun, and Y. A. Nanehkaran, "Using deep transfer learning for image-based plant disease identification," *Comput. Electron. Agricult.*, vol. 173, Jun. 2020, Art. no. 105393.
[21] X. Liu, W. Min, S. Mei, L. Wang, and S. Jiang, "Plant disease recognition: A large-scale benchmark dataset and a visual region and loss reweighting approach," *IEEE Trans. Image Process.*, vol. 30, pp. 2003–2015, 2021.
[22] Z. Gao, L. R. Khot, R. A. Naidu, and Q. Zhang, "Early detection of grapevine leafroll disease in a red-berried wine grape cultivar using hyperspectral imaging," *Comput. Electron. Agricult.*, vol. 179, Dec. 2020, Art. no. 105807.
[23] S. K. Noon, M. Amjad, M. A. Qureshi, and A. Mannan, "Use of deep learning techniques for identification of plant leaf stresses: A review," *Sustain. Comput., Informat. Syst.*, vol. 28, Dec. 2020, Art. no. 100443.
[24] R. Manavalan, "Automatic identification of diseases in grains crops through computational approaches: A review," *Comput. Electron. Agricult.*, vol. 178, Nov. 2020, Art. no. 105802.
[25] Z. Iqbal, M. A. Khan, M. Sharif, J. H. Shah, M. H. ur Rehman, and K. Javed, "An automated detection and classification of citrus plant diseases using image processing techniques: A review," *Comput. Electron. Agricult.*, vol. 153, pp. 12–32, Oct. 2018.
[26] 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.
[27] Y. Tang, Y. Fu, Q. Guo, H. Huang, Z. Tan, and S. Luo, "Numerical simulation of the spatial and temporal distributions of the downwash airflow and spray field of a co-axial eight-rotor plant protection UAV in hover," *Comput. Electron. Agricult.*, vol. 206, Mar. 2023, Art. no. 107634.
[28] 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.
[29] R. I. Hasan, S. M. Yusuf, and L. Alzubaidi, "Review of the state of the art of deep learning for plant diseases: A broad analysis and discussion," *Plants*, vol. 9, no. 10, p. 1302, Oct. 2020.
[30] M. Nagaraju and P. Chawla, "Systematic review of deep learning techniques in plant disease detection," *Int. J. Syst. Assurance Eng. Manage.*, vol. 11, no. 3, pp. 547–560, Jun. 2020.
[31] 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.
[32] J. Lu, L. Tan, and H. Jiang, "Review on convolutional neural network (CNN) applied to plant leaf disease classification," *Agriculture*, vol. 11, no. 8, p. 707, Jul. 2021.
[33] M. M. Ali, N. A. Bachik, N. Muhadi, T. N. T. Yusof, and C. Gomes, "Non-destructive techniques of detecting plant diseases: A review," *Physiolog. Mol. Plant Pathol.*, vol. 108, Dec. 2019, Art. no. 101426.
[34] A. H. Alamoodi, B. B. Zaidan, A. A. Zaidan, S. M. Samuri, A. R. Ismail, O. Zughoul, M. Faiez, G. A. Alshafeay, and M. A. Chyad, "A review of data analysis for early-childhood period: Taxonomy, motivations, challenges, recommendation, and methodological aspects," *IEEE Access*, vol. 7, pp. 51069–51103, 2019.
[35] J. Chen, J. Chen, D. Zhang, Y. A. Nanehkaran, and Y. Sun, "A cognitive vision method for the detection of plant disease images," *Mach. Vis. Appl.*, vol. 32, no. 1, pp. 1–18, Jan. 2021.
[36] J. Ma, K. Du, F. Zheng, L. Zhang, and Z. Sun, "A segmentation method for processing greenhouse vegetable foliar disease symptom images," *Inf. Process. Agricult.*, vol. 6, no. 2, pp. 216–223, Jun. 2019.
[37] G. Yang, G. Chen, Y. He, Z. Yan, Y. Guo, and J. Ding, "Self-supervised collaborative multi-network for fine-grained visual categorization of tomato diseases," *IEEE Access*, vol. 8, pp. 211912–211923, 2020.
[38] M. Lv, G. Zhou, M. He, A. Chen, W. Zhang, and Y. Hu, "Maize leaf disease identification based on feature enhancement and DMS-robust alexnet," *IEEE Access*, vol. 8, pp. 57952–57966, 2020.
[39] H. Ali, M. I. Lali, M. Z. Nawaz, M. Sharif, and B. A. Saleem, "Symptom based automated detection of citrus diseases using color histogram and textural descriptors," *Comput. Electron. Agricult.*, vol. 138, pp. 92–104, Jun. 2017.

[40] Y. Zhong and M. Zhao, "Research on deep learning in apple leaf disease recognition," *Comput. Electron. Agricult.*, vol. 168, Jan. 2020, Art. no. 105146.
[41] W. Haider, A.-U. Rehman, N. M. Durrani, and S. U. Rehman, "A generic approach for wheat disease classification and verification using expert opinion for knowledge-based decisions," *IEEE Access*, vol. 9, pp. 31104–31129, 2021.
[42] T. Rumpf, A.-K. Mahlein, U. Steiner, E.-C. Oerke, H.-W. Dehne, and L. Plümer, "Early detection and classification of plant diseases with support vector machines based on hyperspectral reflectance," *Comput. Electron. Agricult.*, vol. 74, no. 1, pp. 91–99, Oct. 2010.
[43] S. Liaghat, S. Mansor, R. Ehsani, H. Z. M. Shafri, S. Meon, and S. Sankaran, "Mid-infrared spectroscopy for early detection of basal stem rot disease in oil palm," *Comput. Electron. Agricult.*, vol. 101, pp. 48–54, Feb. 2014.
[44] R. Zhou, S. Kaneko, F. Tanaka, M. Kayamori, and M. Shimizu, "Disease detection of Cercospora Leaf Spot in sugar beet by robust template matching," *Comput. Electron. Agricult.*, vol. 108, pp. 58–70, Oct. 2014.
[45] É. A. S. Moriya, N. N. Imai, A. M. G. Tommaselli, and G. T. Miyoshi, "Mapping mosaic virus in sugarcane based on hyperspectral images," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 10, no. 2, pp. 740–748, Feb. 2017.
[46] A. AlSuwaidi, B. Grieve, and H. Yin, "Feature-ensemble-based novelty detection for analyzing plant hyperspectral datasets," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 11, no. 4, pp. 1041–1055, Apr. 2018.
[47] L. M. Griffel, D. Delparte, and J. Edwards, "Using support vector machines classification to differentiate spectral signatures of potato plants infected with potato virus y," *Comput. Electron. Agricult.*, vol. 153, pp. 318–324, Oct. 2018.
[48] S. Pandiyan, M. Ashwin, R. Manikandan, K. M. K. Raghunath, and G. R. A. Raman, "Heterogeneous Internet of Things organization predictive analysis platform for apple leaf diseases recognition," *Comput. Commun.*, vol. 154, pp. 99–110, Mar. 2020.
[49] W. Chen, Y. Lin, F. Ng, C. Liu, and Y. Lin, "RiceTalk: Rice blast detection using Internet of Things and artificial intelligence technologies," *IEEE Internet Things J.*, vol. 7, no. 2, pp. 1001–1010, Feb. 2020.
[50] R. Karthik, M. Hariharan, S. Anand, P. Mathikshara, A. Johnson, and R. Menaka, "Attention embedded residual CNN for disease detection in tomato leaves," *Appl. Soft Comput.*, vol. 86, Jan. 2020, Art. no. 105933.
[51] V. Udutalapally, S. P. Mohanty, V. Pallagani, and V. Khandelwal, "SCrop: A novel device for sustainable automatic disease prediction, crop selection, and irrigation in Internet-of-Agro-Things for smart agriculture," *IEEE Sensors J.*, vol. 21, no. 16, pp. 17525–17538, Aug. 2021.
[52] J. P. Rodríguez, A. I. Montoya-Munoz, C. Rodriguez-Pabon, J. Hoyos, and J. C. Corrales, "IoT-agro: A smart farming system to Colombian coffee farms," *Comput. Electron. Agricult.*, vol. 190, Nov. 2021, Art. no. 106442.
[53] M. Mishra, P. Choudhury, and B. Pati, "Modified ride-NN optimizer for the IoT based plant disease detection," *J. Ambient Intell. Humanized Comput.*, vol. 12, no. 1, pp. 691–703, Jan. 2021.
[54] N. Kundu, G. Rani, V. S. Dhaka, K. Gupta, S. C. Nayak, S. Verma, M. F. Ijaz, and M. Woźniak, "IoT and interpretable machine learning based framework for disease prediction in pearl millet," *Sensors*, vol. 21, no. 16, p. 5386, Aug. 2021.
[55] D. Sarpal, R. Sinha, M. Jha, and P. Tn, "AgriWealth: IoT based farming system," *Microprocessors Microsyst.*, vol. 89, Mar. 2022, Art. no. 104447.
[56] P. Chen, W. Li, S. Yao, C. Ma, J. Zhang, B. Wang, C. Zheng, C. Xie, and D. Liang, "Recognition and counting of wheat mites in wheat fields by a three-step deep learning method," *Neurocomputing*, vol. 437, pp. 21–30, May 2021.
[57] A. Johannes, A. Picon, A. Alvarez-Gila, J. Echazarra, S. Rodriguez-Vaamonde, A. D. Navajas, and A. Ortiz-Barredo, "Automatic plant disease diagnosis using mobile capture devices, applied on a wheat use case," *Comput. Electron. Agricult.*, vol. 138, pp. 200–209, Jun. 2017.
[58] A. M. Abdu, M. M. Mokji, and U. U. Sheikh, "Automatic vegetable disease identification approach using individual lesion features," *Comput. Electron. Agricult.*, vol. 176, Sep. 2020, Art. no. 105660.
[59] K. K. Chakraborty, R. Mukherjee, C. Chakroborty, and K. Bora, "Automated recognition of optical image based potato leaf blight diseases using deep learning," *Physiolog. Mol. Plant Pathol.*, vol. 117, Jan. 2022, Art. no. 101781.
[60] C. Hou, J. Zhuang, Y. Tang, Y. He, A. Miao, H. Huang, and S. Luo, "Recognition of early blight and late blight diseases on potato leaves based on graph cut segmentation," *J. Agricult. Food Res.*, vol. 5, Sep. 2021, Art. no. 100154.
[61] H. F. Pardede, E. Suryawati, R. Sustika, and V. Zilvan, "Unsupervised convolutional autoencoder-based feature learning for automatic detection of plant diseases," in *Proc. Int. Conf. Comput., Control, Informat. Appl. (IC3INA)*, Nov. 2018, pp. 158–162.
[62] 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.
[63] P. Jiang, Y. Chen, B. Liu, D. He, and C. Liang, "Real-time detection of apple leaf diseases using deep learning approach based on improved convolutional neural networks," *IEEE Access*, vol. 7, pp. 59069–59080, 2019.
[64] M. A. Khan, M. I. U. Lali, M. Sharif, K. Javed, K. Aurangzeb, S. I. Haider, A. S. Altamrah, and T. Akram, "An optimized method for segmentation and classification of apple diseases based on strong correlation and genetic algorithm based feature selection," *IEEE Access*, vol. 7, pp. 46261–46277, 2019.
[65] H. Sun, H. Xu, B. Liu, D. He, J. He, H. Zhang, and N. Geng, "MEAN-SSD: A novel real-time detector for apple leaf diseases using improved light-weight convolutional neural networks," *Comput. Electron. Agricult.*, vol. 189, Oct. 2021, Art. no. 106379.
[66] H.-J. Yu and C.-H. Son, "Leaf spot attention network for apple leaf disease identification," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. Workshops (CVPRW)*, Jun. 2020, pp. 52–53.
[67] U. Barman, R. D. Choudhury, D. Sahu, and G. G. Barman, "Comparison of convolution neural networks for smartphone image based real time classification of citrus leaf disease," *Comput. Electron. Agricult.*, vol. 177, Oct. 2020, Art. no. 105661.
[68] S. Dananjayan, Y. Tang, J. Zhuang, C. Hou, and S. Luo, "Assessment of state-of-the-art deep learning based citrus disease detection techniques using annotated optical leaf images," *Comput. Electron. Agricult.*, vol. 193, Feb. 2022, Art. no. 106658.
[69] J. Chen, W. Wang, D. Zhang, A. Zeb, and Y. A. Nanehkaran, "Attention embedded lightweight network for maize disease recognition," *Plant Pathol.*, vol. 70, no. 3, pp. 630–642, Apr. 2021.
[70] A. Darwish, D. Ezzat, and A. E. Hassanien, "An optimized model based on convolutional neural networks and orthogonal learning particle swarm optimization algorithm for plant diseases diagnosis," *Swarm Evol. Comput.*, vol. 52, Feb. 2020, Art. no. 100616.
[71] K. Garg, S. Bhugra, and B. Lall, "Automatic quantification of plant disease from field image data using deep learning," in *Proc. IEEE Winter Conf. Appl. Comput. Vis. (WACV)*, Jan. 2021, pp. 1964–1971.
[72] S. Hernández and J. L. López, "Uncertainty quantification for plant disease detection using Bayesian deep learning," *Appl. Soft Comput.*, vol. 96, Nov. 2020, Art. no. 106597.
[73] 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.
[74] A. Waheed, M. Goyal, D. Gupta, A. Khanna, A. E. Hassanien, and H. M. Pandey, "An optimized dense convolutional neural network model for disease recognition and classification in corn leaf," *Comput. Electron. Agricult.*, vol. 175, Aug. 2020, Art. no. 105456.
[75] A. Abbas, S. Jain, M. Gour, and S. Vankudothu, "Tomato plant disease detection using transfer learning with C-GAN synthetic images," *Comput. Electron. Agricult.*, vol. 187, Aug. 2021, Art. no. 106279.
[76] V. Gonzalez-Huitron, J. A. León-Borges, A. E. Rodriguez-Mata, L. E. Amabilis-Sosa, B. Ramírez-Pereda, and H. Rodriguez, "Disease detection in tomato leaves via CNN with lightweight architectures implemented in raspberry pi 4," *Comput. Electron. Agricult.*, vol. 181, Feb. 2021, Art. no. 105951.
[77] 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.
[78] H. Nazki, S. Yoon, A. Fuentes, and D. S. Park, "Unsupervised image translation using adversarial networks for improved plant disease recognition," *Comput. Electron. Agricult.*, vol. 168, Jan. 2020, Art. no. 105117.
[79] J. Zhou, J. Li, C. Wang, H. Wu, C. Zhao, and Q. Wang, "A vegetable disease recognition model for complex background based on region proposal and progressive learning," *Comput. Electron. Agricult.*, vol. 184, May 2021, Art. no. 106101.

[80] M. Ji, L. Zhang, and Q. Wu, "Automatic grape leaf diseases identification via UnitedModel based on multiple convolutional neural networks," *Inf. Process. Agricult.*, vol. 7, no. 3, pp. 418–426, Sep. 2020.

[81] M. Ji and Z. Wu, "Automatic detection and severity analysis of grape black measles disease based on deep learning and fuzzy logic," *Comput. Electron. Agricult.*, vol. 193, Feb. 2022, Art. no. 106718.

[82] P. Kaur, H. S. Pannu, and A. K. Malhi, "Plant disease recognition using fractional-order Zernike moments and SVM classifier," *Neural Comput. Appl.*, vol. 31, no. 12, pp. 8749–8768, Dec. 2019.

[83] M. Kerkech, A. Hafiane, and R. Canals, "Vine disease detection in UAV multispectral images using optimized image registration and deep learning segmentation approach," *Comput. Electron. Agricult.*, vol. 174, Jul. 2020, Art. no. 105446.

[84] Y. Li, J. Nie, and X. Chao, "Do we really need deep CNN for plant diseases identification?" *Comput. Electron. Agricult.*, vol. 178, Nov. 2020, Art. no. 105803.

[85] B. Liu, C. Tan, S. Li, J. He, and H. Wang, "A data augmentation method based on generative adversarial networks for grape leaf disease identification," *IEEE Access*, vol. 8, pp. 102188–102198, 2020.

[86] Z. Tang, J. Yang, Z. Li, and F. Qi, "Grape disease image classification based on lightweight convolution neural networks and channelwise attention," *Comput. Electron. Agricult.*, vol. 178, Nov. 2020, Art. no. 105735.

[87] 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.

[88] Q. H. Cap, H. Tani, S. Kagiwada, H. Uga, and H. Iyatomi, "LASSR: Effective super-resolution method for plant disease diagnosis," *Comput. Electron. Agricult.*, vol. 187, Aug. 2021, Art. no. 106271.

[89] Q. H. Cap, H. Uga, S. Kagiwada, and H. Iyatomi, "LeafGAN: An effective data augmentation method for practical plant disease diagnosis," *IEEE Trans. Autom. Sci. Eng.*, vol. 19, no. 2, pp. 1258–1267, Apr. 2022.

[90] J. Ma, K. Du, L. Zhang, F. Zheng, J. Chu, and Z. Sun, "A segmentation method for greenhouse vegetable foliar disease spots images using color information and region growing," *Comput. Electron. Agricult.*, vol. 142, pp. 110–117, Nov. 2017.

[91] C. Wang, P. Du, H. Wu, J. Li, C. Zhao, and H. Zhu, "A cucumber leaf disease severity classification method based on the fusion of DeepLabV3+ and U-Net," *Comput. Electron. Agricult.*, vol. 189, Oct. 2021, Art. no. 106373.

[92] S. Zhang and Z. Wang, "Cucumber disease recognition based on global-local singular value decomposition," *Neurocomputing*, vol. 205, pp. 341–348, Sep. 2016.

[93] S. Zhang, X. Wu, Z. You, and L. Zhang, "Leaf image based cucumber disease recognition using sparse representation classification," *Comput. Electron. Agricult.*, vol. 134, pp. 135–141, Mar. 2017.

[94] S. Zhang, S. Zhang, C. Zhang, X. Wang, and Y. Shi, "Cucumber leaf disease identification with global pooling dilated convolutional neural network," *Comput. Electron. Agricult.*, vol. 162, pp. 422–430, Jul. 2019.

[95] S. Zhang, Y. Zhu, Z. You, and X. Wu, "Fusion of superpixel, expectation maximization and PHOG for recognizing cucumber diseases," *Comput. Electron. Agricult.*, vol. 140, pp. 338–347, Aug. 2017.

[96] P. Zhang, L. Yang, and D. Li, "EfficientNet-B4-ranger: A novel method for greenhouse cucumber disease recognition under natural complex environment," *Comput. Electron. Agricult.*, vol. 176, Sep. 2020, Art. no. 105652.

[97] N. V. R. R. Goluguri, K. S. Devi, and P. Srinivasan, "Rice-Net: An efficient artificial fish swarm optimization applied deep convolutional neural network model for identifying the Oryza sativa diseases," *Neural Comput. Appl.*, vol. 33, no. 11, pp. 5869–5884, Jun. 2021.

[98] F. Jiang, Y. Lu, Y. Chen, D. Cai, and G. Li, "Image recognition of four Rice leaf diseases based on deep learning and support vector machine," *Comput. Electron. Agricult.*, vol. 179, Dec. 2020, Art. no. 105824.

[99] Y. Lu, S. Yi, N. Zeng, Y. Liu, and Y. Zhang, "Identification of Rice diseases using deep convolutional neural networks," *Neurocomputing*, vol. 267, pp. 378–384, Dec. 2017.

[100] A. Nigam, A. K. Tiwari, and A. Pandey, "Paddy leaf diseases recognition and classification using PCA and BFO-DNN algorithm by image processing," *Mater. Today, Proc.*, vol. 33, pp. 4856–4862, 2020.

[101] S. Phadikar, J. Sil, and A. K. Das, "Rice diseases classification using feature selection and rule generation techniques," *Comput. Electron. Agricult.*, vol. 90, pp. 76–85, Jan. 2013.

[102] S. Radhakrishnan, "An improved machine learning algorithm for predicting blast disease in paddy crop," *Mater. Today, Proc.*, vol. 33, pp. 682–686, Jan. 2020.

[103] C. R. Rahman, P. S. Arko, M. E. Ali, M. A. I. Khan, S. H. Apon, F. Nowrin, and A. Wasif, "Identification and recognition of Rice diseases and pests using convolutional neural networks," *Biosyst. Eng.*, vol. 194, pp. 112–120, Jun. 2020.

[104] S. Ramesh and D. Vydeki, "Recognition and classification of paddy leaf diseases using optimized deep neural network with Jaya algorithm," *Inf. Process. Agricult.*, vol. 7, no. 2, pp. 249–260, Jun. 2020.

[105] S. Sengupta and A. K. Das, "Particle swarm optimization based incremental classifier design for Rice disease prediction," *Comput. Electron. Agricult.*, vol. 140, pp. 443–451, Aug. 2017.

[106] P. K. Sethy, N. K. Barpanda, A. K. Rath, and S. K. Behera, "Deep feature based Rice leaf disease identification using support vector machine," *Comput. Electron. Agricult.*, vol. 175, Aug. 2020, Art. no. 105527.

[107] V. Tiwari, R. C. Joshi, and M. K. Dutta, "Dense convolutional neural networks based multiclass plant disease detection and classification using leaf images," *Ecolog. Informat.*, vol. 63, Jul. 2021, Art. no. 101289.

[108] Y. Wang, H. Wang, and Z. Peng, "Rice diseases detection and classification using attention based neural network and Bayesian optimization," *Expert Syst. Appl.*, vol. 178, Sep. 2021, Art. no. 114770.

[109] G. Zhou, W. Zhang, A. Chen, M. He, and X. Ma, "Rapid detection of Rice disease based on FCM-KM and faster R-CNN fusion," *IEEE Access*, vol. 7, pp. 143190–143206, 2019.

[110] J. Chen, D. Zhang, M. Suzauddola, Y. A. Nanehkaran, and Y. Sun, "Identification of plant disease images via a squeeze-and-excitation MobileNet model and twice transfer learning," *IET Image Process.*, vol. 15, no. 5, pp. 1115–1127, Apr. 2021.

[111] R. Gozzovelli, B. Franchetti, M. Bekmurat, and F. Pirri, "Tip-burn stress detection of lettuce canopy grown in plant factories," in *Proc. IEEE/CVF Int. Conf. Comput. Vis. Workshops (ICCVW)*, Oct. 2021, pp. 1259–1268.

[112] J. Wang, L. Yu, J. Yang, and H. Dong, "DBA_SSD: A novel end-to-end object detection algorithm applied to plant disease detection," *Information*, vol. 12, no. 11, p. 474, Nov. 2021.

[113] W. Zeng and M. Li, "Crop leaf disease recognition based on self-attention convolutional neural network," *Comput. Electron. Agricult.*, vol. 172, May 2020, Art. no. 105341.

[114] X. Chen, G. Zhou, A. Chen, J. Yi, W. Zhang, and Y. Hu, "Identification of tomato leaf diseases based on combination of ABCK-BWTR and B-ARNet," *Comput. Electron. Agricult.*, vol. 178, Nov. 2020, Art. no. 105730.

[115] J. Chen, D. Zhang, M. Suzauddola, and A. Zeb, "Identifying crop diseases using attention embedded MobileNet-V2 model," *Appl. Soft Comput.*, vol. 113, Dec. 2021, Art. no. 107901.

[116] Y. Zhao, C. Sun, X. Xu, and J. Chen, "RIC-Net: A plant disease classification model based on the fusion of inception and residual structure and embedded attention mechanism," *Comput. Electron. Agricult.*, vol. 193, Feb. 2022, Art. no. 106644.

[117] S. Gutiérrez, I. Hernández, S. Ceballos, I. Barrio, A. M. Díez-Navajas, and J. Tardaguila, "Deep learning for the differentiation of downy mildew and spider mite in grapevine under field conditions," *Comput. Electron. Agricult.*, vol. 182, Mar. 2021, Art. no. 105991.

[118] 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.

[119] K. Kc, Z. Yin, M. Wu, and Z. Wu, "Depthwise separable convolution architectures for plant disease classification," *Comput. Electron. Agricult.*, vol. 165, Oct. 2019, Art. no. 104948.

[120] G. Geetharamani and A. Pandian, "Identification of plant leaf diseases using a nine-layer deep convolutional neural network," *Comput. Electr. Eng.*, vol. 76, pp. 323–338, Jun. 2019.

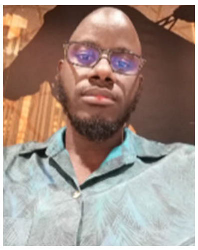
[121] A. Karlekar and A. Seal, "SoyNet: Soybean leaf diseases classification," *Comput. Electron. Agricult.*, vol. 172, May 2020, Art. no. 105342.

[122] Z. Li, Y. Yang, Y. Li, R. Guo, J. Yang, and J. Yue, "A solanaceae disease recognition model based on SE-inception," *Comput. Electron. Agricult.*, vol. 178, Nov. 2020, Art. no. 105792.

[123] P. Sharma, Y. P. S. Berwal, and W. Ghai, "Performance analysis of deep learning CNN models for disease detection in plants using image segmentation," *Inf. Process. Agricult.*, vol. 7, no. 4, pp. 566–574, Dec. 2020.

[124] S. Xiang, Q. Liang, W. Sun, D. Zhang, and Y. Wang, "L-CSMS: Novel lightweight network for plant disease severity recognition," *J. Plant Diseases Protection*, vol. 128, no. 2, pp. 557–569, Apr. 2021.
[125] M. Agarwal, S. K. Gupta, and K. K. Biswas, "Development of efficient CNN model for tomato crop disease identification," *Sustain. Comput., Informat. Syst.*, vol. 28, Dec. 2020, Art. no. 100407.
[126] K. P. Ferentinos, "Deep learning models for plant disease detection and diagnosis," *Comput. Electron. Agricult.*, vol. 145, pp. 311–318, Feb. 2018.
[127] J. G. A. Barbedo, "Impact of dataset size and variety on the effectiveness of deep learning and transfer learning for plant disease classification," *Comput. Electron. Agricult.*, vol. 153, pp. 46–53, Oct. 2018.
[128] S. Coulibaly, B. Kamsu-Foguem, D. Kamissoko, and D. Traore, "Deep neural networks with transfer learning in millet crop images," *Comput. Ind.*, vol. 108, pp. 115–120, Jun. 2019.
[129] S. H. Lee, H. Goëau, P. Bonnet, and A. Joly, "New perspectives on plant disease characterization based on deep learning," *Comput. Electron. Agricult.*, vol. 170, Mar. 2020, Art. no. 105220.
[130] Y. Xiong, L. Liang, L. Wang, J. She, and M. Wu, "Identification of cash crop diseases using automatic image segmentation algorithm and deep learning with expanded dataset," *Comput. Electron. Agricult.*, vol. 177, Oct. 2020, Art. no. 105712.
[131] K. Deeba and B. Amutha, "WITHDRAWN: ResNet–deep neural network architecture for leaf disease classification," *Microprocessors Microsystems*, vol. 78, Oct. 2020, Art. no. 103364.
[132] Ü. Atila, M. Uçar, K. Akyol, and E. Uçar, "Plant leaf disease classification using EfficientNet deep learning model," *Ecolog. Informat.*, vol. 61, Mar. 2021, Art. no. 101182.
[133] P. Singh, A. Verma, and J. S. R. Alex, "Disease and pest infection detection in coconut tree through deep learning techniques," *Comput. Electron. Agricult.*, vol. 182, Mar. 2021, Art. no. 105986.
[134] J. W. Clohessy, S. Sanjel, G. K. O'Brien, R. Barocco, S. Kumar, S. Adkins, B. Tillman, D. L. Wright, and I. M. Small, "Development of a high-throughput plant disease symptom severity assessment tool using machine learning image analysis and integrated geolocation," *Comput. Electron. Agricult.*, vol. 184, May 2021, Art. no. 106089.
[135] Q. Zeng, X. Ma, B. Cheng, E. Zhou, and W. Pang, "GANs-based data augmentation for citrus disease severity detection using deep learning," *IEEE Access*, vol. 8, pp. 172882–172891, 2020.
[136] J. Abdulridha, Y. Ampatzidis, R. Ehsani, and A. I. de Castro, "Evaluating the performance of spectral features and multivariate analysis tools to detect laurel wilt disease and nutritional deficiency in avocado," *Comput. Electron. Agricult.*, vol. 155, pp. 203–211, Dec. 2018.
[137] E. C. Too, L. Yujian, S. Njuki, and L. Yingchun, "A comparative study of fine-tuning deep learning models for plant disease identification," *Comput. Electron. Agricult.*, vol. 161, pp. 272–279, Jun. 2019.
[138] R. Sujatha, J. M. Chatterjee, N. Jhanjhi, and S. N. Brohi, "Performance of deep learning vs machine learning in plant leaf disease detection," *Microprocessors Microsyst.*, vol. 80, Feb. 2021, Art. no. 103615.
[139] Q. Liang, S. Xiang, Y. Hu, G. Coppola, D. Zhang, and W. Sun, "PD2SE-Net: Computer-assisted plant disease diagnosis and severity estimation network," *Comput. Electron. Agricult.*, vol. 157, pp. 518–529, Feb. 2019.
[140] G. Hu, H. Wu, Y. Zhang, and M. Wan, "A low shot learning method for tea leaf's disease identification," *Comput. Electron. Agricult.*, vol. 163, Aug. 2019, Art. no. 104852.
[141] D. Argüeso, A. Picon, U. Irusta, A. Medela, M. G. San-Emeterio, A. Bereciartua, and A. Alvarez-Gila, "Few-shot learning approach for plant disease classification using images taken in the field," *Comput. Electron. Agricult.*, vol. 175, Aug. 2020, Art. no. 105542.
[142] U. Fang, J. Li, X. Lu, L. Gao, M. Ali, and Y. Xiang, "Self-supervised cross-iterative clustering for unlabeled plant disease images," *Neurocomputing*, vol. 456, pp. 36–48, Oct. 2021.
[143] M. Turkoglu, B. Yanikoğlu, and D. Hanbay, "PlantDiseaseNet: Convolutional neural network ensemble for plant disease and pest detection," *Signal, Image Video Process.*, vol. 16, no. 2, pp. 301–309, Mar. 2022.
[144] L. Goyal, C. M. Sharma, A. Singh, and P. K. Singh, "Leaf and spike wheat disease detection & classification using an improved deep convolutional architecture," *Informat. Med. Unlocked*, vol. 25, Jan. 2021, Art. no. 100642.
[145] R. Alguliyev, Y. Imamverdiyev, L. Sukhostat, and R. Bayramov, "Plant disease detection based on a deep model," *Soft Comput.*, vol. 25, no. 21, pp. 13229–13242, Nov. 2021.
[146] P. Gui, W. Dang, F. Zhu, and Q. Zhao, "Towards automatic field plant disease recognition," *Comput. Electron. Agricult.*, vol. 191, Dec. 2021, Art. no. 106523.
[147] A. K. Rangarajan, R. Purushothaman, and M. Pérez-Ruiz, "Disease classification in aubergine with local symptomatic region using deep learning models," *Biosyst. Eng.*, vol. 209, pp. 139–153, Sep. 2021.
[148] Y. Yuan, Z. Xu, and G. Lu, "SPEDCCNN: Spatial pyramid-oriented encoder–decoder cascade convolution neural network for crop disease leaf segmentation," *IEEE Access*, vol. 9, pp. 14849–14866, 2021.
[149] J. Shin, Y. K. Chang, B. Heung, T. Nguyen-Quang, G. W. Price, and A. Al-Mallahi, "A deep learning approach for RGB image-based powdery mildew disease detection on strawberry leaves," *Comput. Electron. Agricult.*, vol. 183, Apr. 2021, Art. no. 106042.
[150] R. D. L. Pires, D. N. Gonçalves, J. P. M. Oruê, W. E. S. Kanashiro, J. F. Rodrigues, B. B. Machado, and W. N. Gonçalves, "Local descriptors for soybean disease recognition," *Comput. Electron. Agricult.*, vol. 125, pp. 48–55, Jul. 2016.
[151] S. S. Chouhan, A. Kaul, U. P. Singh, and S. Jain, "Bacterial foraging optimization based radial basis function neural network (BRBFNN) for identification and classification of plant leaf diseases: An automatic approach towards plant pathology," *IEEE Access*, vol. 6, pp. 8852–8863, 2018.
[152] Y. Sun, Z. Jiang, L. Zhang, W. Dong, and Y. Rao, "SLIC_SVM based leaf diseases saliency map extraction of tea plant," *Comput. Electron. Agricult.*, vol. 157, pp. 102–109, Feb. 2019.
[153] J. M. M. Araujo and Z. M. A. Peixoto, "A new proposal for automatic identification of multiple soybean diseases," *Comput. Electron. Agricult.*, vol. 167, Dec. 2019, Art. no. 105060.
[154] H. Hamdani, A. Septiarini, A. Sunyoto, S. Suyanto, and F. Utaminingrum, "Detection of oil palm leaf disease based on color histogram and supervised classifier," *Optik*, vol. 245, Nov. 2021, Art. no. 167753.
[155] N. Kaur, "Plant leaf disease detection using ensemble classification and feature extraction," *Turkish J. Comput. Math. Educ. (TURCOMAT)*, vol. 12, no. 11, pp. 2339–2352, 2021.
[156] C. Milhorance, F. Howland, E. Sabourin, and J.-F. L. Coq, "Tackling the implementation gap of climate adaptation strategies: Understanding policy translation in Brazil and Colombia," *Climate Policy*, vol. 22, nos. 9–10, pp. 1113–1129, Nov. 2022.
[157] P. S. Thakur, P. Khanna, T. Sheorey, and A. Ojha, "Trends in vision-based machine learning techniques for plant disease identification: A systematic review," *Expert Syst. Appl.*, vol. 208, Dec. 2022, Art. no. 118117.
[158] R. Thapa, K. Zhang, N. Snavely, S. Belongie, and A. Khan, "The plant pathology challenge 2020 data set to classify foliar disease of apples," *Appl. Plant Sci.*, vol. 8, no. 9, Sep. 2020, Art. no. e11390.
[159] X. Nie, L. Wang, H. Ding, and M. Xu, "Strawberry verticillium wilt detection network based on multi-task learning and attention," *IEEE Access*, vol. 7, pp. 170003–170011, 2019.
[160] D. Wang, J. Wang, W. Li, and P. Guan, "T-CNN: Trilinear convolutional neural networks model for visual detection of plant diseases," *Comput. Electron. Agricult.*, vol. 190, Nov. 2021, Art. no. 106468.
[161] D. Mathew, C. S. Kumar, and K. A. Cherian, "Foliar fungal disease classification in banana plants using elliptical local binary pattern on multiresolution dual tree complex wavelet transform domain," *Inf. Process. Agricult.*, vol. 8, no. 4, pp. 581–592, Dec. 2021.
[162] Y. Yuan, L. Chen, M. Li, N. Wu, L. Wan, and S. Wang, "Diagnosis of nitrogen nutrition of Rice based on image processing of visible light," in *Proc. IEEE Int. Conf. Functional-Structural Plant Growth Modeling, Simulation, Visualizat. Appl. (FSPMA)*, Nov. 2016, pp. 228–232.
[163] M. A. Khan, T. Akram, M. Sharif, M. Awais, K. Javed, H. Ali, and T. Saba, "CCDF: Automatic system for segmentation and recognition of fruit crops diseases based on correlation coefficient and deep CNN features," *Comput. Electron. Agricult.*, vol. 155, pp. 220–236, Dec. 2018.
[164] S. S. Chouhan, A. Kaul, and U. P. Singh, "Radial basis function neural network for the segmentation of plant leaf disease," in *Proc. 4th Int. Conf. Inf. Syst. Comput. Netw. (ISCON)*, Nov. 2019, pp. 713–716.
[165] D. Mondal, D. K. Kole, and K. Roy, "Gradation of yellow mosaic virus disease of okra and bitter gourd based on entropy based binning and naive Bayes classifier after identification of leaves," *Comput. Electron. Agricult.*, vol. 142, pp. 485–493, Nov. 2017.
[166] J. G. A. Barbedo, "Factors influencing the use of deep learning for plant disease recognition," *Biosyst. Eng.*, vol. 172, pp. 84–91, Aug. 2018.
[167] A. Sinha and R. S. Shekhawat, "A novel image classification technique for spot and blight diseases in plant leaves," *Imag. Sci. J.*, vol. 68, no. 4, pp. 225–239, May 2020.

[168] M. M. Agrawal and S. Agrawal, "Rice plant diseases detection & classifiation using deep learning models: A systematic review," *J. Crit. Rev.*, vol. 7, no. 11, pp. 4376–4390, 2020.
[169] J. Boulent, S. Foucher, J. Théau, and P.-L. St-Charles, "Convolutional neural networks for the automatic identification of plant diseases," *Frontiers Plant Sci.*, vol. 10, p. 941, Jul. 2019.
[170] S. Li, K. Li, Y. Qiao, and L. Zhang, "A multi-scale cucumber disease detection method in natural scenes based on YOLOv5," *Comput. Electron. Agricult.*, vol. 202, Nov. 2022, Art. no. 107363.
[171] A. I. Khan, S. M. K. Quadri, S. Banday, and J. L. Shah, "Deep diagnosis: A real-time apple leaf disease detection system based on deep learning," *Comput. Electron. Agricult.*, vol. 198, Jul. 2022, Art. no. 107093.
[172] A. Dhakal and S. Shakya, "Image-based plant disease detection with deep learning," *Int. J. Comput. Trends Technol.*, vol. 61, no. 1, pp. 26–29, Jul. 2018.
[173] P. Mishra, G. Polder, and N. Vilfan, "Close range spectral imaging for disease detection in plants using autonomous platforms: A review on recent studies," *Current Robot. Rep.*, vol. 1, no. 2, pp. 43–48, Jun. 2020.
[174] S. S. Sannakki, V. S. Rajpurohit, V. B. Nargund, and P. Kulkarni, "Diagnosis and classification of grape leaf diseases using neural networks," in *Proc. 4th Int. Conf. Comput., Commun. Netw. Technol. (ICCCNT)*, Jul. 2013, pp. 1–5.
[175] S. Prasad, S. K. Peddoju, and D. Ghosh, "Multi-resolution mobile vision system for plant leaf disease diagnosis," *Signal, Image Video Process.*, vol. 10, no. 2, pp. 379–388, Feb. 2016.
[176] 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. 507–524, Feb. 2022.



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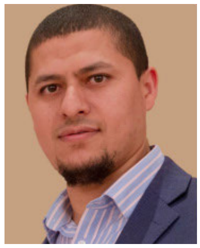

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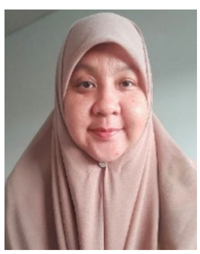

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