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Retraction

Retracted: A Systematic Analysis of Machine Learning and Deep Learning Based Approaches for Plant Leaf Disease Classification: A Review

Journal of Sensors

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope

(2) Discrepancies in the description of the research reported

(3) Discrepancies between the availability of data and the research described

(4) Inappropriate citations

(5) Incoherent, meaningless and/or irrelevant content included in the article

(6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] R. Kumar, A. Chug, A. P. Singh, and D. Singh, "A Systematic Analysis of Machine Learning and Deep Learning Based Approaches for Plant Leaf Disease Classification: A Review," *Journal of Sensors*, vol. 2022, Article ID 3287561, 13 pages, 2022.

Review Article

A Systematic Analysis of Machine Learning and Deep Learning Based Approaches for Plant Leaf Disease Classification: A Review

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Crops' production and quality of yields are heavily affected by crop diseases which cause adverse impacts on food security as well as economic losses. In India, agriculture is a prime source of income in most rural areas. Hence, there is an intense need to employ novel and accurate computer vision-based techniques for automatic crop disease detection and their classification so that prophylactic actions can be recommended in a timely manner. In literature, numerous computer vision-based techniques by utilizing divergent combinations of machine learning, deep learning, CNN, and various image-processing techniques along with their associated merits and demerits have already been discussed. In this study, we systematically reviewed recent research studies undertaken by a variety of scholars and researchers of fungal and bacterial plant disease detection and classification and summarized them based on vital parameters like type of crop utilized, deep learning/machine learning architecture used, dataset utilized for experiments, performance matrices, types of disease detected and classified, and highest accuracy achieved by the model. As per the analysis carried out, in the category of machine learning-based approaches, 70% of studies utilized real-field plant leaf images and 30% utilized laboratory condition plant leaf images for disease classification while in the case of deep learning-based approaches, 55% studied employed laboratory-conditioned images from the PlantVillage dataset, 25% utilized real-field images, and 20% utilized open image datasets. The average accuracy attained with deep learning-based approaches is quite higher at 98.8% as compared to machine learning-based approaches at 92.2%. In the case of deep learning-based methods, we also analyzed the performances of pretrained and training from scratch models that have been utilized in various studies for plant leaf disease classification. Pretrained models perform better with 99.64% classification accuracy compared to training from scratch models which achieved 98.64% average accuracy. We also highlighted some major issues encountered in the computer vision-based disease detection and classification approach used in literature and provided recommendations that will help and guide researchers to explore new dimensions in crop disease recognition.

1. Introduction

Agriculture is a key income stream for the majority of Indians who live in remote or semiurban areas [1]. Also, the agricultural sector significantly contributes to the Indian economy. Infection in crops may cause significant degradation in crop yields as well as quality [2]. So, early disease detection, prevention, and management are very crucial. At the current stage, various computer vision-based automatic disease detection systems have already been proposed by

several researchers [3]. The era of modern agriculture is changing constantly and can be categorized into two periods: 1943 to 2006, when deep learning and threshold concepts were introduced, and the second from 2012 to now. In the first span of evolution, numerous innovations took place like Back Propagation, Chain Rule, Neocognitron, and LeNet (handwritten text recognition), and in the second phase, various futuristic deep learning architectures like AlexNet, VGG, ZFNet, GoogLeNet, ResNet, SegNet, YOLO, U-Net, Fast R-CNN, and Mask R-CNN had already been

proposed for numerous applications like image recognition, self-driving car, and healthcare [4], and their performances were analyzed using different performance matrices like accuracy, precision, recall, and F1-score.

A bunch of studies has been done over the last few years by utilizing diverse image-processing techniques with different deep learning-based models on a variety of plant diseases, of which some are depicted in Figure 1, on varieties of datasets. Some issues were encountered while working with deep learning/machine learning models: most of the studies (around 80.00%) have utilized laboratory-conditioned datasets like PlantVillage datasets, for the aim of training and evaluation. The model was developed using pictures that had been generated in a lab and generally fails to generalize(very less accuracy as compared to laboratory-conditioned images) on real-field images [5]. Other issues are as follows, for example: real-field backgrounds for plant photos can be quite complicated, which may significantly affect the performance of the model being used; sometimes, features may not be visible or may be overlapped with other features, so in this case, appropriate feature extraction and selection is a major challenge [6]. Other than categorization and diagnosis of crop diseases, measurement of disease severity level is much more important for early disease detection and remedial action in the field [7].

During this study, we compiled and analyzed several recent deep learning- and machine learning-based techniques for plant disease diagnostics. We also highlighted major issues encountered. The disease detection challenge has been overcome to a great extent due to the advent of revolutionary models/architectures in the domain of plant disease detection, but still, there are some issues like lack of real-field image datasets, data annotation, and prelabeling for early-stage disease detection, precise infected area/symptom identification, and extraction in the case of similarity among different disease symptoms, precise stage-wise severity estimation, and efficiency of deep learning models being used [8]. So, inventive methods with refined precision on real-field images are extremely essential for crop protection and disease diagnosis so that potential problems may be avoided.

The following is how the rest of the study is structured: we summed up the general methodology for plant disease detection and classification in Section II; the outline of the major factors responsible for plant diseases is in Section III; the literature review conducted on machine learning and deep learning models is in Section IV, and we conclude with specific suggestions in Section V.

2. A Short Introduction to Plant Disease Recognition and Classification

Computer vision is the subdomain of artificial intelligence which permits machines to counterfeit the human visual system and enable them to precisely draw out, inspect, and recognize real-world images like a human being does. Most growing sectors, such as medical diagnosis, espionage, satellite imagery, and agribusiness, have already demonstrated the value of computer vision-based technologies. Computer

vision-enabled systems can be put into the agriculture domain to effectively detect and classify plant diseases based on different disease features or symptoms extracted. Computer vision-based systems employ a well-defined series of steps starting from image acquisition followed by various image-processing tasks including scaling, filtering, segmentation, feature extraction, and selection, and finally, detection and classification are done through machine learning or approaches based on deep learning [9]. Figure 2 depicts the full procedure used by most computer vision-based techniques to recognize and classify plant diseases.

3. Factors Responsible for Plant Diseases

A wide range of agricultural diseases can occur at various phases of a plant's development and hurt the plant's growth which may result in detrimental influences on overall crop production. There are numerous factors responsible for plant diseases at different stages of plant development. As shown in Figure 3, factors responsible for crop diseases are divided into two major categories: one is biotic factors and another is abiotic factors. Biotic factors like viruses, fungus, bacteria, mites, and slugs develop due to microbial infection in plants whereas abiotic factors cause harm to plants' growth due to environmental factors like water, temperature, irradiation, and nutrient deficiency.

4. Literature Review

We explored a variety of recent computer vision-based plant disease detection and classification algorithms in this study. The algorithms under investigation have been divided into two main categories: machine learning (ML) and deep learning (DL). The first section of the literature review summarizes the machine learning-based techniques and the second part summarizes deep learning-based techniques. We also presented a comparative analysis of the investigated algorithms in a tabular form.

4.1. Machine Learning-Based Techniques. This section describes recent machine learning-based plant disease detection and classification techniques.

By combining the deployment of the moth-flame optimization technique with the idea of rough sets, a tomato plant disease detection technique was proposed [10]. The combination of moth-flame with rough sets helps to improve the accuracy of the proposed algorithm, and performance was evaluated against PSO and genetic algorithm using the rough sets. Ref. [6] presented a diseased image classification method that first divided the input image into superpixels, and then, a k-means algorithm for clustering was applied to extract each superpixel's lesion image, to form clusters. After segmentation, features were extracted from three elements of the color of each segmented lesion image and used for further disease leaf recognition tasks on the classification model. A genetic algorithm-based leaf disease recognition and classification approach for color leaf image segmentation was introduced in [11]. This study performed the classification task in two steps: first, it classified
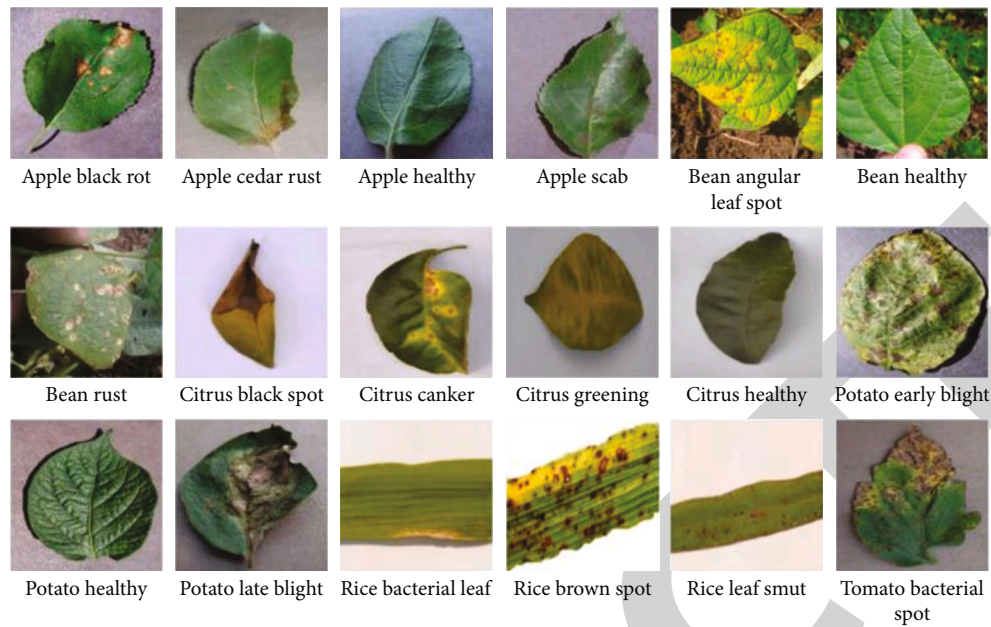
FIGURE 1: Some sample plant leaf images with different diseases from the PlantVillage dataset.
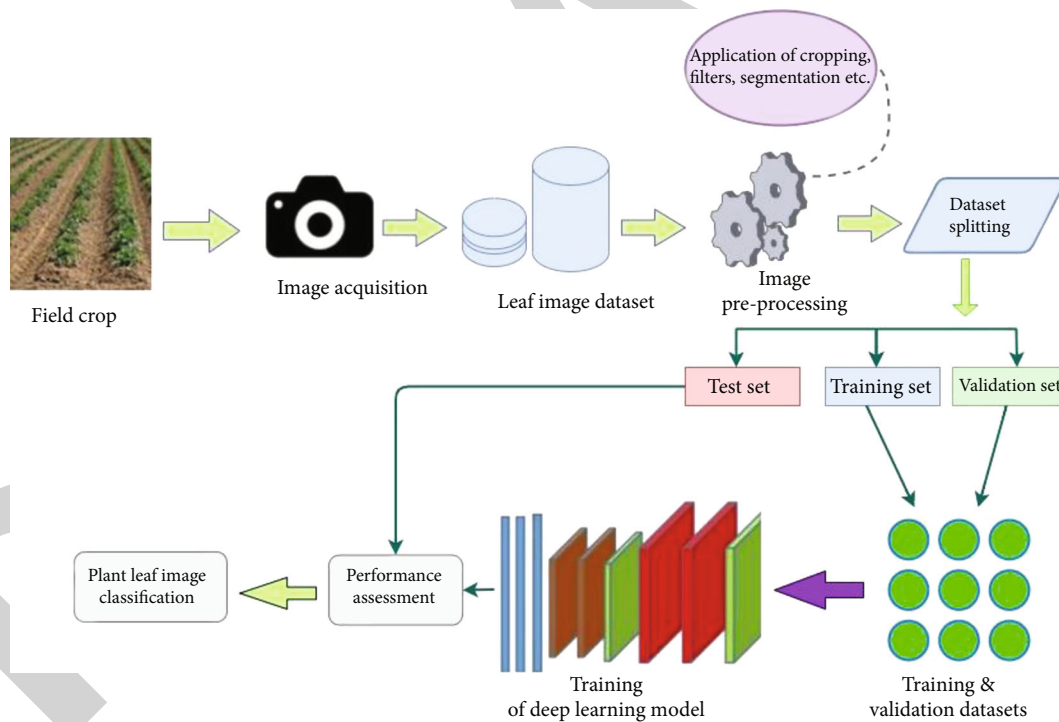

FIGURE 2: Computer vision-based approach to plant disease detection and classification [9].

using *K*-means clustering through minimum distance criteria, and afterward, it utilized SVM for the second phase classification, which increased its classification accuracy from 86.54% to 95.71%. A neural network-based classifier: the radial basis function neural network (RBFNN), for the detection and classification of two rice diseases, named rice blast and the brown spot, was proposed [12]. The study first used the principal component analysis (PCA) algorithm to reduce the dimensions of an input image, and then, features like colors, shape, and texture of diseased leaves of the rice plant are extracted for disease detection and classification using the RBFNN classifier, and performance was evaluated using accuracy, precision, and recall metrics. Ref. [7] discussed the classification and severity measurement of diseases on cucumber leaves. In this, first, the input image quality was enhanced through preprocessing, and then,
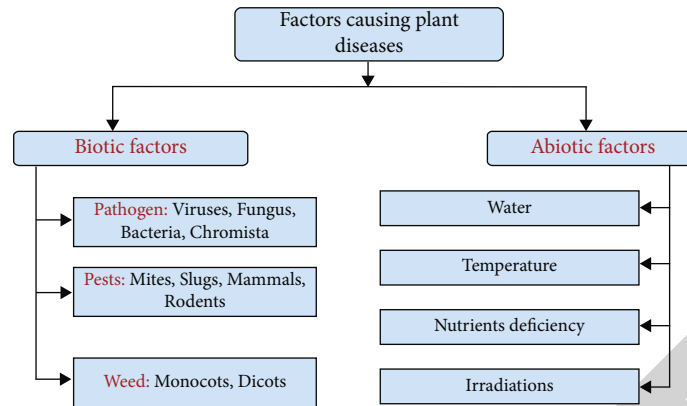
Figure 3: Factors responsible for plant diseases [4].

segmentation was done through the *K*-means algorithm. The segmented image was then used for classification via the machine learning technique, and severity was measured using the damaged area divided by the total area of the plant's leaf. Ref. [2] discussed KNN and ANN-based blast disease diagnosis and categorization techniques for paddy. The input image was segmented using *K*-means clustering, and then, appropriate parameters such as mean value, standard deviation, energy, homogeneity, entropy, and the gray level cooccurrence matrix (GLCM) were retrieved from the segmented image. These segmented features were applied to KNN and ANN classifiers for disease classification. As results show, ANN outperforms KNN.

Ref. [13] presented an Extreme Learning Machine (ELM) algorithm for disease classification on the Tomato Powdery Mildew Dataset (TPMD) imbalanced dataset. For balancing the dataset, the researchers used four distinct resampling techniques. As shown in the results, the ELM algorithm was run on both imbalanced and balanced datasets, and performance has been evaluated using the classification accuracy and AUC curve. The performance of the algorithm is better on the balanced dataset, and among the four resampling techniques used, the Extreme Learning Machine (ELM) algorithm outperforms Importance Sampling (IMS) with a classification accuracy of 89.19% and AUC of 88.57%. Ref. [14] discussed the application of capsule networks on potato leaves for the classification of two diseases (early and late blight) in potato plants. The studies used the PlantVillage dataset, and the results obtained were compared against some pretrained models—ResNet18, VGG16, and GoogleLetNet, which were also trained on the same dataset. As results show, capsule networks (CapsNet) do a better job with an accuracy of 91.83%, as compared to pretrained CNN models. Ref. [15] outlined the combined application of the SVM and logistic regression classifier together on real-time data of the Tomato Powdery Mildew Disease dataset. Before applying the hybrid SVM-LR classifier, it first balances the dataset using random oversampling and, afterward, divides the dataset into training (70%) and test (30%) datasets. The proposed SVM-LR classifier is applied in two phases—the first phase involves noise reduction, which is carried out by SVM with adaptive sampling-based noise reduction (ANR); after this, logistic regression

(LR) is applied on the modified dataset produced in phase 1 for disease classification. Furthermore, the performance of the proposed method can be improved by incorporating feature selection and optimization techniques. Ref. [3], based on color features alone, presented a disease detection and classification model for rice plants. In this, seven output classes—six disease classes and a healthy class—have been considered. The efficacy of seven distinct classifiers, such as SVM, discriminant analysis, KNN, Naive-Bayes, Decision Trees, Random Forest, and Logistic Regression, against the performance matrices, like accuracy, sensitivity, specificity, AUC, ROC, and F1-score, was also compared and assessed in this study. SVM outperforms all classifiers with the highest classification accuracy 94.65

4.1.1. Table 1 Analysis. As summarized in Table 1, various types of plant cultures like tomato, banana, cucumber, apple, rose, mango, lemon, and rice potato with diverse datasets have been investigated by various researchers for identification and diagnosis using machine learning (ML) techniques. In the next section, we have a parameter-wise analysis of Table 1.

As depicted in Figures 4–7 and Tables 2–5, we further analyzed the parameters like crop type, type of classifier used, dataset utilized by the study, and the highest accuracy achieved by the classifier. After this parameter-wise analysis, we can conclude that most of the studies summarized in Table 1 are being conducted on tomato or rice plants and have utilized the PlantVillage dataset for experimental purposes. Most of the machine learning- (ML-) based approaches adopted support vector machine (SVM) or *K*-means classifier for classification purposes.

Most of the ML-based classification approaches used real-field image datasets for training and testing purposes. But the real-field image datasets are of limited size which in general may affect the training of the model being used. So another issue in the real-field image dataset is the size of the dataset. The accuracy of those ML-based methods that used some kind of segmentation/clustering as a preprocessing step is quite higher than that of others. So, appropriate segmentation and other preprocessing steps could significantly improve the quality of input that may improve the performance of classifiers.

Table 1: Machine learning-based methods: a comparative analysis.

| Crop culture	Methods used	Performance metrics	Dataset	Accuracy (%)	Reference
Tomato plant	Moth-flame optimization & genetic algorithm	Recall, precision, accuracy, F1-score	UCI machine learning repository	86	[10]
Apple & cucumber plant	K-means clustering and PHOG	Recognition rate	Real-field images	90.43 & 92.15	[6]
Plant leaves (like rose, lemon, mango, and banana)	K-means clustering, genetic algorithm, SVM	Accuracy	Real conditioned capture images	95.71	[11]
Rice plant	Radial basis function neural network	Accuracy, precision, recall	Real-field images	95.0	[12]
Cucumber plant	K-means clustering, SVM	Accuracy	Real-field images	86	[7]
Rice crop	KNN, ANN	Accuracy	Real-field images	86 & 99	[2]
Tomato plant	Extreme Learning Machine (ELM)	Accuracy, AUC	Tomato powdery mildew dataset (TPMD)	89.19	[13]
Potato leaves	Capsule networks (CapsNet)	Accuracy	Plant village dataset	91.83	[14]
Tomato plant	SVM & logistic regression (SVM-LR)	Accuracy, AUC, F1-score	Real-time data of tomato powdery mildew disease dataset	92.73	[15]
Rice plant	SVM	Accuracy, sensitivity, specificity, AUC, ROC, F1-score	Real-field images	94.65	[3]
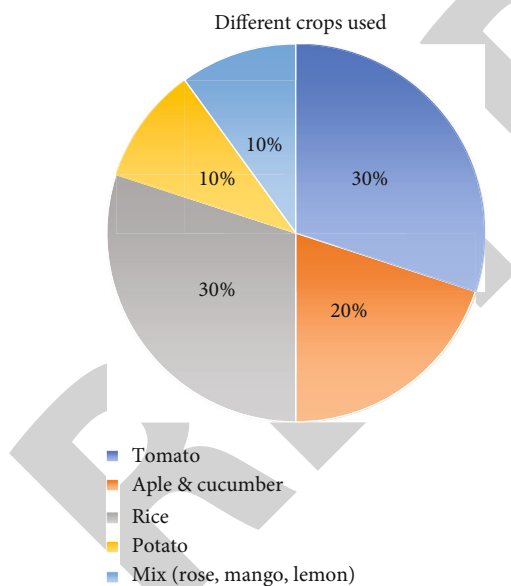
Figure 4: Different crops utilized.

4.2. Deep Learning-Based Approaches.

This section of the literature review outlines the summary of different recent deep learning-based algorithms that have been implemented for plant disease detection and classification in recent times.

AlexNet, AlexNetOWTBn, GoogLeNet, OverFeat, and VGG are five CNN models that were experimented on an open dataset comprising around 87,848 images of 25 different crops with 58 different classes of (plant, disease) pairs, and their performances were analyzed. Two models VGG and AlexNetOWTBn with the highest success rate were selected for further training and testing on real images. As results showed, some preliminary results with real conditioned data manifested a significant performance reduction (25-35%), and models performed better when trained on real images and tested on laboratory images. Among all the models tested, VGG had the greatest success rate of 99.53 percent [8, 16]. In this study, two CNN baseline models, the ResNet50 and ResNet50 with aggregated nonimage contextual information, were trained and tested on the dataset of a hundred-thousand real conditioned images having seventeen diseases of five different crops captured through cellphones. Models were first trained on the ImageNet dataset, and then, they were retrained and validated on the real conditioned dataset developed with these pretrained initialization weights. As results showed, the performance of the models was similar for both large datasets with multiple crops and split datasets for different crops. Ref. [5] proposed CNN-based models for plant disease diagnosis by utilizing an object detection architecture alongside VGG16, ResNet50, MobileNet, ResNet101, and for Fast R-CNN and Mask R-CNN. Fast R-CCN was used for disease detection and Mask R-CNN for segmenting the affected diseased area. The study also used different annotation mechanisms with object detection. Labeling was used with Fast R-CNN and LabelMe with Mask R-CNN. ResNet101 had the best detection rate but required the most training and testing time, while MobileNet took the fastest time but was less precise than ResNet101. So, based on the scenario at hand, the best model could opt. Ref. [17] analyzed the use of deep learning
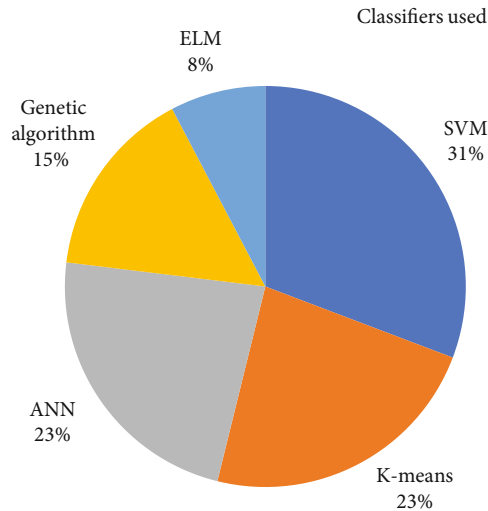
Classifiers used

Figure 5: Types of classifiers used.

Datasets used

- Real filed images
- Plantvillage dataset
- UCI machine learning repository
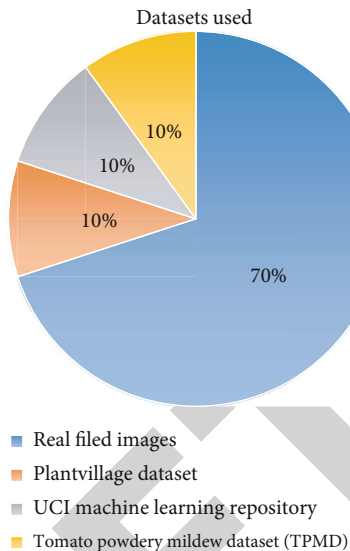- Tomato powdery mildew dataset (TPMD)

Figure 6: Datasets used in ML-based approaches.

models for plant disease diagnosis and discovered some challenges and factors that influence the models' effectiveness. Some of these factors are related to datasets used in the study, and others are intrinsic to plant diseases. Dataset-related issues were limited to annotated dataset, symptom representations, covariate shift, image background, and capture conditions. In contrast, the factors intrinsic to the issue included system segmentation, symptom variations, simultaneous disorders, and disorders with similar symptoms. All mentioned factors could significantly affect the performance if not properly taken care of. Ref. [18] outlined the application of the CNN model on the PlantVillage dataset for the identification of diseases of various types of plants including apple, grape, corn, and tomato. Augmentation on the dataset was also applied to maintain a balance between different classes. Ref. [19] came up with a method for plant leaf image classification that first detects edges

using a Canny edge detector and then classifies detected edges using shallow CNN into two classes: background edge or plant edge. After this, it further subclassifies plant edges into three classes: plant edge, leaf edge, and internal image noise. It further used region-based segmentation used to convert edges into leaf images for leaf counting purposes. The proposed approach could be quite effective for CNN with binary classification (background segmentation). Ref. [20] gave a comprehensive list of various deep learning models that have been employed for crop disease diagnosis in recent times, along with a comparative evaluation of their strengths and drawbacks. The study mainly classified the identification models into two categories—one without visualization and another with visualization techniques—and also highlighted some of the visualization techniques used for symptom recognition.

In [21], to classify the diverse tomato plant illnesses, a deep learning architecture with an integrated whale optimization algorithm was proposed and experimented on with the PlantVillage image dataset. The proposed method first applied one-hot encoding to convert categorical data of images into binary digits (0 or 1) and then PCA to minimize the dimensionality of the input dataset and choose the most acceptable features for prediction; whale optimization strategy has been used. A grid search hyperparameter tuning technique was used to tune hyperparameters for performance optimization. Ref. [22] discussed the application of ResNet50, for tomato plant disease classification using data augmentation and transformation to generate a large dataset from the given original dataset to boost the classification system's performance and also reduce the chances of overfitting. For classification, the model classified two stages: in the first stage, it classified the leaf as either healthy or unhealthy, and if it is unhealthy, it is classified as a disease in the second stage. Ref. [23] highlighted the use of three different CNN models, AlexNet, SqueezeNet, and Inception V3, to determine the degree of late blight pathogenicity in tomato plants in the early, middle, and end-stages, utilizing a dataset of several types of tomato leaf imagery from the PlantVillage dataset. For better performance, implementation of models was carried out in two ways—feature extraction and transfer learning wherein the multiclass support vector machine was trained using the retrieved features. Finally, the study evaluated the performance of all three models against the parameters, i.e., the accuracy of the classifier, mean F1-score, and recall. Ref. [24] proposed a generic feature-based disease detection method using residual network ResNet50 architecture, which was further incorporated with disease severity measurement based on proportional disease damaged area of the leaf for greenhouse tomato plants. Generic features enable good generalization on unseen instances of the dataset. The study also outlined and compared the results of different variations of models, featuring a binary categorization system for sick and healthy leaves and another with ten class (9 for different types of diseases and 1 for healthy leaf) outputs, trained and tested on different augmented image datasets. The study's findings revealed that a model with a binary class (healthy and diseased) does better generalization than the 10-class model,
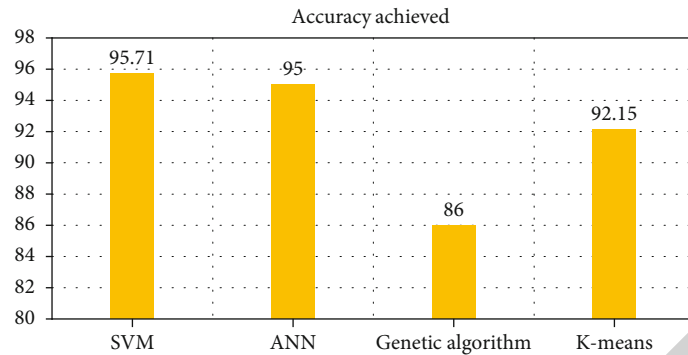
FIGURE 7: Accuracy comparison of different classifiers used in ML-based approaches.

TABLE 2: Different crops used.

Crop type	Number of studies
Tomato	3
Apple & cucumber	2
Rice	3
Potato	1
Mix (rose, mango, lemon)	1

TABLE 3: Types of classifiers used.

Classifier name	Accuracy achieved (%)
SVM	95.71
ANN	95
Genetic algorithm	86
K-means	92.15

TABLE 4: Variety of datasets utilized.

Name of dataset	Number of studies used
Real-field images	7
PlantVillage dataset	1
UCI machine learning repository	1
Tomato powdery mildew dataset (TPMD)	1

TABLE 5: Highest accuracy achieved.

Type of classifier	Frequency
SVM	4
K-means	3
ANN	3
Genetic algorithm	2
ELM	1

and diseased leaves can be identified by their shape only. And also, the proportional disease-damaged area method used for severity detection is only suitable for discrete and localized symptoms that are generally caused by diseases like fungi and by bacterial spots. It is not suitable for systematic symptoms such as virus symptoms like progressive chlorosis, leaf curl, and stunting

In [25], the study proposed a residual CNN learning-based architecture with an integrated attention mechanism for disease identification in tomato plant leaves from the PlantVillage dataset. This architecture gives more weightage to the context-relevant features by assigning more weights compared to other less significant features, which significantly affect the performance of the model. The study used a k-way SoftMax classifier for input image classification. Finally, the study compared the results of experiments conducted using a 5-fold cross-validation on the PlantVillage dataset, of three CNN models—baseline CNN, residual CNN, and attention-embedded residual CNN which provide 84%, 95%, and 98% of accuracy, respectively [26]. The effectiveness of four pretrained CNN models for tomato plant disease detection was evaluated using two datasets: lab setting and fields. For performance evaluation, the study conducted 8-8 experiments (4 with pretrained parameters and 4 with parameter tunning) using 10-fold cross-validation. For each dataset, F1-score, precision, accuracy, and recall performance indicators were generated and compared. As per the results shown, all four models perform better (10-15% better) on laboratory datasets as compared to field datasets, and among the four models being presented, Inception V3 outperforms with 99.6% and 93.6% accuracy on laboratory and field datasets, respectively. Ref. [27] presented an application of CNN with hierarchical feature extraction for disease detection in tomato plant leaves. Before applying segmentation and feature extraction, it first used Gaussian filters to remove noise from input images. After this preprocessing, a CNN classifier was applied that classified the dataset into two classes—healthy leaves or diseased leaves. As per the results of the experiment shown, the CNN classifier performs better than AlexNet and ANN. Ref. [28] presented a crop disease identification method based on visual disease features independent of crop species. For experimental purposes, three different algorithms—GoogLeNet, VGG16, and Inception V3—were trained and evaluated on distinct

TABLE 6: Deep learning-based methods: a comparative view.

Crop culture	Method used	Performance metrics	Dataset	Accuracy (%)	Reference
25 different plants (apple, grape, banana, cherry, etc.)	CNN-AlexNet, AlexNetOWTBn, GoogLeNet, OverFeat, and VGG	Success rate	Open dataset	99.53 (VGG)	[8]
Multicrops (wheat, barley, corn, rice, and rapeseed)	ResNet50 with contextual information	Accuracy	Real-field images	98.0	[16]
Tomato	Fast R-CNN & Mask R-CNN with VGG16, ResNet50, ResNet101, and MobileNet	Average precision	Internet images	99.64 (ResNet101)	[5]
Multiple plants (like apple, grape, corn, tomato, etc.)	CNN	Accuracy	PlantVillage dataset	96.5	[18]
Arabidopsis plants	Shallow CNN & Canny edge detector	The difference in count (DIC), foreground/background dice (FBD), symmetric best dice (SBD)	Aberystwyth leaf evaluation dataset (ALED)	95	[19]
Tomato leaves	PCA-whale optimization & DNN	Accuracy and loss rate	PlantVillage dataset	86	[21]
Tomato leaves	ResNet50	Accuracy	PlantVillage dataset	97	[22]
Tomato leaves	CNN-AlexNet, SqueezeNet, Inception V3, and SVM	Accuracy, recall, F1-score	PlantVillage dataset	AlexNet-93.40, SqueezeNet-90.76, Inception V3-90.43	[23]
Tomato leaves	ResNet and U-Net	Accuracy	PlantVillage dataset	94	[24]
Tomato leaves	CNN with an attention mechanism	Accuracy	PlantVillage dataset	98	[25]
Tomato leaves	CNN models—VGG16, VGG19, ResNet, Inception V3	Accuracy, precision, recall, F1-score	Laboratory & field datasets	(Inception V3) 99.6 & 93.6	[26]
Multiple common disease types	GoogLeNet, VGG16, Inception V3	Accuracy	PlantVillage dataset	98 (VGG16)	[28]
14 different plant species	EfficientNet	Accuracy, sensitivity, specificity, precisions	PlantVillage dataset	98.4	[29]
Tomato leaves	CNN with 4 hidden layers	Accuracy, precision, recall, F1-score	PlantVillage dataset	Average 91.2	[30]
Tomato leaves	CNN with KijaniNet (modified segmentation network)	Mean accuracy, mean boundary F1-score	Real conditioned dataset	98.46	[31]
Grape leaves	Enhanced ANN and CNN	Accuracy and F1-score	PlantVillage dataset	93.75	[32]
Tomato leaves	Region-based CNN (R-CNN)	Average precision, confusion matrix	Real-field images	83.06	[33]
Banana leaves	CNN with a total generalized variation fuzzy C-means segmentation	Sensitivity, specificity, accuracy	Real-field images	93.45	[34]
Maize plant leaves	CNN-AlexNet	Accuracy	PlantVillage dataset	99.16	[35]
Mix crop leaves (wheat, corn, cotton, grape, and cucumber)	CNN-AlexNet with PSO optimization	Sensitivity, specificity, accuracy, precision, F1-score	Real-field images	98.83	[36]

imagery of common disease kinds from PlantVillage dataset itself, with transfer learning and training on dataset approaches. As per the result shown, models showed better generalization on the common disease dataset on unseen diseased images as compared to disease-crop strategy, and among three models, VGG16 outperformed.

Ref. [29] proposed the EfficientNet deep learning architecture which is a family of eight models B0 to B7, to classify

TABLE 7: Dataset usage.

Type of datasets	Frequency of usage
Real-field images	5
PlantVillage dataset	11
Open dataset/internet images	4

TABLE 8: Different classifiers used.

Type of classifiers	Frequency of usage
DNN/CNN with optimization	3
Pretrained model	11
DNN/CNN with segmentation	4
DNN trained from scratch	3

TABLE 9: Highest accuracy achieved with different deep learning-based classifiers.

Type of classifier	Highest accuracy (%)
DNN/CNN with optimization	98.83
Pretrained model	99.64
DNN/CNN with segmentation	98.46
DNN trained from scratch	96.5
Model with real-field images	98

and detect plant diseases by utilizing the PlantVillage dataset with augmentation. Instead of ReLU, the suggested model employs Swish, a novel activation function. The results were compared to those of other prominent deep learning models. The performance of the model was assessed using the parameters like accuracy, sensitivity, specificity, and precision. As results showed, B5 and B4 models outperformed with resultant accuracy of 98.84% and 99.39% on original and augmented datasets, respectively. Ref. [30] came up with a CNN-based model which was applied to the PlantVillage dataset with augmentation, for plant disease identification and classification. Experiments were conducted with nine diseases and one healthy class, and results were compared with pretrained models like VGG16, Inception V3, and MobileNet. The proposed CNN model outperformed with a testing accuracy of 91.2%.

In [31], first, two segmentation schemes were evaluated in terms of performance-U-Net and SegNet on a real conditioned image dataset for background removal, and based on performance, U-Net was picked up and its encoder phases were altered based on multiscale disease feature retrieval and named as KijaniNet. The performance of the proposed architecture was evaluated against pretrained models. KijaniNet showed better results as compared to U-Net and SegNet on realistic condition image datasets. Ref. [32] suggested a model for detecting plant diseases which included segmentation and classification. The study first uses region-based segmentation to effectively extract disease spots from the grape plant leaf images and also separates them from complex backgrounds, and then, for further categorization, segmented visuals are put into a CNN-based model. Applying segmentation as preprocessing on disease images helps to achieve better accuracy.

4.2.1. Table 6 Analysis. Table 6 summarizes a parameter-by-parameter examination of deep learning-based studies. From this tabular data, we further explored the investigation of types of crops used, nature and type of classifiers, kind of datasets Table 7, and the highest accuracy achieved by different classes of classifiers. The majority of the deep learning-(DL-) based methods used convolution neural network (CNN) or a variant of CNN as their base model, see Table 8, for detecting and classifying plant diseases with the PlantVillage dataset (see Table 9 and Figure 8). Most of the research work summarized in Table 6 utilized pretrained deep learning models (see Table 8 and Figure 9) on tomato leaf image (see Table 10 and Figure 10) classification, and 99.64 percent precision was attained with the utilization of pretrained deep learning models (see Table 9 and Figure 11). Also, the performance of the models that employed some kind of image preprocessing techniques like segmentation, filtering,
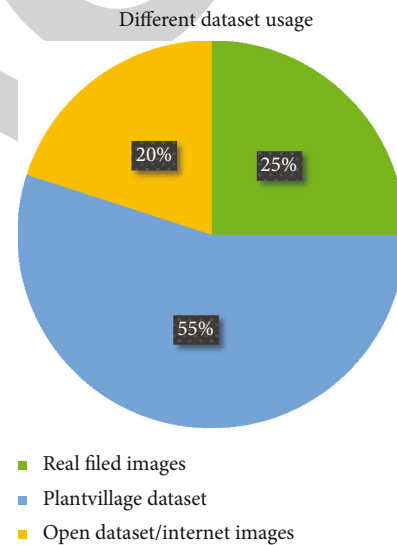

Different dataset usage

FIGURE 8: Proportion of different datasets utilized.

or integration of some contextual information to better segregate the lesion area of the image or some kind of optimization for feature extraction and selection, to the input image to deep learning model, is quite higher (around 98.43 and 98.46, see Table 9) than others. Another noticeable point is that the performance of models that utilized real-field images is comparatively low (see Table 9 and Figure 11).

So, with deep learning models, there are two points of consideration—one, we should have quite a large dataset of relevant plant images for effective training and generalization on real-field images. The other is that there should be some kind of image preprocessing or optimization heuristic for feature extraction and selection to effectively detect and segment the lesion area from an input plant leaf image.
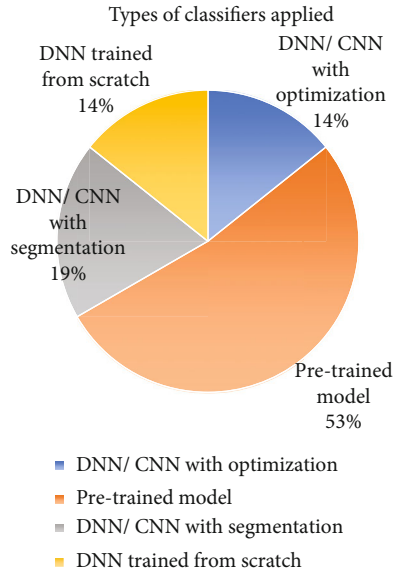
Types of classifiers applied

Figure 9: Proportion of classifiers used.

Table 10: Crop types with usage frequency.

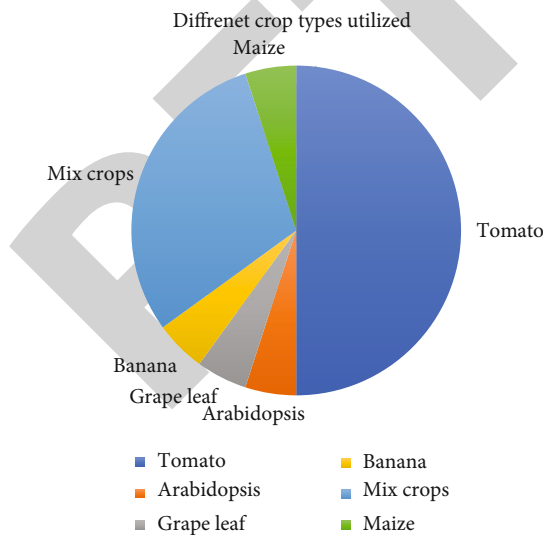| Crop type	Frequency of usage
Tomato	10
Arabidopsis	1
Grape leaf	1
Banana	1
Mix crops	6
Maize	1

Diffrenet crop types utilized

Figure 10: Crops used in deep learning-based approaches.

4.3. Detection and Classification of Plant Diseases: Key Issues. Followed by a detailed and critical study of numerous recent machine learning- and deep learning-based approaches developed for plant disease recognition and classification in the literature, we have summarized a few important challenges in crop disease recognition and classification that will enable the researcher's community to explore the causes that may greatly impact real-time-based systems for plant identification and diagnosis. Some factors and issues may affect disease identification and classification; most of them are listed below:

(a) The performance of plant disease detection systems mainly depends on disease features, their extraction, and the type of classifiers used [2]

(b) Most of the studies utilized laboratory-conditioned image datasets like the PlantVillage dataset rather than real-field image datasets. The performance of the classifiers used was heavily affected by the kind of dataset used for training and testing purposes [2]

(c) Background removal and segmentation of the diseased area from leaf imagery are critical as real-field images may have different complex backgrounds, which significantly affect the performance of the detection model [18]

(d) Estimation of the infected area and severity measurement along with detection task could be used to control the usage of pesticides [23]

(e) It is tough to tell if the plant has an infection or is deficient in minerals or nutrients [37]

(f) Because a plant can be contaminated at any stage of its development, so early disease detection is critical [38]

(g) The efficiency of the model employed for real-time illness detection on resource-constrained devices should be considered [24]

(h) Most illness symptoms do not have obvious borders and instead blend into normal tissue, making it difficult to distinguish between healthy and sick parts [16]

(i) Distinct diseases may create different manifestations at the same time, so it will be difficult to identify, separate, or combine them into hybrid symptoms (coexistence of multiple diseases on the same leaf) [21]

(j) Appropriate selection and tunning of hyperparameters have the potential to have a significant influence on performance [32]

(k) The performance of computer vision-based disease detection and classification systems is greatly influenced by image capture, preprocessing, lesion fragmentation, extraction of features, and the classifiers being utilized [37]

(l) Due to the uniformity of disease characteristics, contaminated regions, and selection of appropriate attributes, disease recognition systems face significant challenges [39]
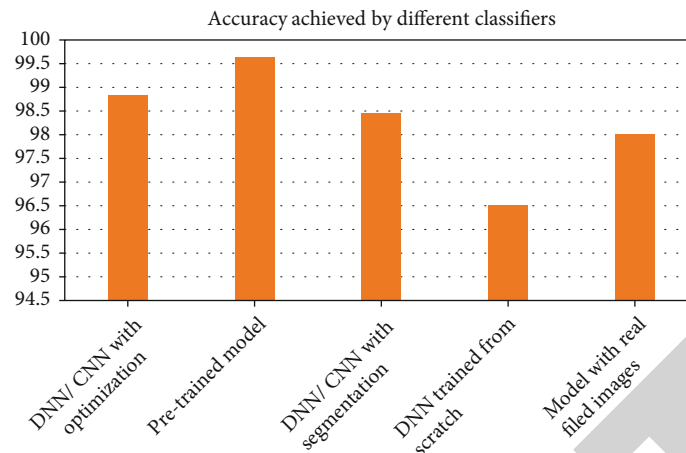
FIGURE 11: Accuracy comparison of different classifiers in deep learning-based approaches.

5. Conclusion and Recommendations

Computer vision-based systems employ a well-defined series of steps starting from image acquisition followed by various image-processing tasks including scaling, filtering, segmentation, selection, and extraction of features, and eventually, machine learning- or deep learning-based algorithms are used for recognition and classification. We also looked at a variety of current research studies that used machine learning- or deep learning-based algorithms to recognize and analyze plant diseases. Further, we presented parameterwise dissection for the parameters like type of crop used, classifiers used, nature of datasets, and highest accuracy achieved by different classes of classifiers. We also presented some statistics about the research works summarized in Tables 1–6 through Tables 2–5, Tables 10–9, and Figures 4–8. We presented a systematic analysis of recent machine learning- or deep learning-based studies for plant disease detection and classification. As per our investigation conducted, 53% (see Figure 10) of deep learning-based studies utilized pretrained models for plant leaf image classification, and around 33% of studies utilized some kind of segmentation or optimization with deep learning models for performance improvement. In the case of machine learning-based approaches, 70% (majority) of the studies employed real-field images, while in deep learning-based approaches, majority (55%) of studies utilized laboratory-conditioned images from the PlantVillage dataset. The performances of both machine learning and deep learning models on real-field mages are not as good as those on laboratory-conditioned images, and deep learning models achieved much higher accuracy (99.64%) compared to machine learning models (95.71%). So, deep learning models are a better choice for image classification tasks as compared to machine learning-based approaches. But some issue remains unresolved as machine learning and deep learning models' performance heavily depend on the training of the underlying model used for classification purpose, and most of the studies in the literature have used laboratory-conditioned image datasets like the PlantVillage dataset and UCI machine learning repository. A model trained on a laboratory-conditioned image dataset generally does not give good generalization on real-field images. So, for better generalization on real-conditioned images of diseased plant leaves, researchers should first collect a sufficient number of real-conditioned images for the model's training and testing. Also, the quality and quantity of relevant characteristics that are fed into the model affect the performance of the model to a great extent. So if one is using some deep learning model, then, we suggest using the appropriate segmentation technique to effectively segment the lesion from the entire leaf image and extract only relevant features from the segmented lesion. This may help to improve performance and reduce the number of irrelevant input features.

We also highlighted some of the important issues associated with plant disease recognition and categorization that may have a significant impact on the model's performance. This work will help the research community to understand the factors which may significantly affect the performance, and researchers will be guided to investigate new aspects in the agricultural disease recognition and classification area via a real-time-based system.

Data Availability

The data relating to the study will be available from the corresponding author (raj0697@gmail.com) upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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