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# Review of the State of the Art of Transfer Learning for Plant Leaf Diseases Detection

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**Abstract**— Plant leaf diseases can have a significantly negative influence on the quantity and quality of agricultural cultivation, as well as the safety of food production. Plant leaf diseases could potentially entirely prevent the harvest of grains in some situations. Therefore, it is extremely important from a pragmatic standpoint to look for quick, automatic, cheap, and accurate ways to detect plant leaf diseases. One of the well-known plant leaf disease detection approaches is deep learning. Deep learning has several drawbacks as a result of the huge amount of data required to train the network. When a dataset has inadequate photographs, performance falls. An approach called "Transfer Learning" is an extensively used method for addressing the shortcomings of a small dataset, the length of the training process, and improving the performance of the model. In this study, we investigated transfer learning for deep CNNs to improve the learning capability to recognize leaf disease. This survey focuses on categorizing and analyzing the recent developments in transfer learning for Deep CNN situations to enhance learning performance by reducing the need for extensive training data collecting.

**Keywords**- transfer learning, the computational procedure of plant leaf disease using transfer learning, CNN architecture literature review, conclusion.

## I. INTRODUCTION

An agricultural harvest's output has a substantial impact on how well a country's economy performs. Diseases, pests, and environmental factors are only a few of the variables that affect the growth and yield of crops. One of the most important elements that significantly lower crop quality is crop leaf disease[1]. Early detection of crop leaf diseases is one of the most crucial agricultural practices. Every year, disease-related infection causes farmers to experience significant financial losses. Therefore, prompt, accurate, and speedy identification of the illness prevents product loss and boosts product quality. It is advantageous to detect plant illnesses using an automatic method since it lessens the amount of work required for crop monitoring in huge agricultural fields and does so at an extremely early stage when symptoms first develop on plant leaves[2]They greatly influence how decisions are made and how agricultural output is managed. However, up until now, the prime method for detecting plant diseases in rural areas of developing countries has been through experienced producers' visual observations[3]. This necessitates continual professional supervision, which in large farms may be prohibitively expensive.

Many earlier efforts have examined picture acknowledgement, and a specific classifier is employed to divide the photos into healthy and unhealthy ones. The symptoms of the majority of plant diseases may first emerge on the leaf, which is typically the first place to look for them when identifying diseases in plants. Utilizing machine learning combined with image processing, several researchers have proposed to identify and categorize plant diseases. These methods attempt to develop disease classifiers utilizing crop picture data. These classifiers are based on manually created features that professionals intended to collect pertinent data for image categorization. These classifiers struggle with a lack of automation because they depend on manually created features. Furthermore, professional picture labels must be used to train the classifier.

Ref [4] discussed the problem associated with the background of leaf image, Capture conditions, well-defined disease boundaries etc. problems that cause hurdles to generate desired features in collected image data. Furthermore, producing labelled data manually following particular selection criteria is difficult and costly[5]. Transfer learning seeks to address this issue by recognizing and putting to use the skills and knowledge acquired via earlier assignments.

Due to its outcomes surpassing the state-of-the-art in many categories, Transfer Learning has gained popularity among computer vision experts in recent years. The primary benefit of Transfer Learning in plant disease Detection is the direct utilization of images without any manually created features. The creation of features via transfer learning classifiers, which are

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complete systems, is done entirely automatically and without the assistance of human subject matter experts.

In this article, we've examined and tracked the development of an automation system based on transfer learning to boost learning efficiency while minimizing time- and money-consuming data-labelling activities. This research is structured as follows: An overview of Transfer Learning methods for Plant leaf detection is given in Section 2, The Computational Procedure for Identifying and Classifying Plant Leaf Diseases is described in Section 3 of the article, A review of the literature and a comparative analysis is presented in Section 4, and the contributions of this study are enumerated in Section 5.

## II OVERVIEW OF TRANSFER LEARNING

Although conventional machine learning technology has been highly successful and employed in various hands-on bids, it still has a few limitations for particular real-world situations. Conventional machine learning techniques presumptively use the same domain for both training and testing data, as well as the data dispersal characteristics and same input feature space [6] Gathering adequate training data, however, is frequently exclusive, laborious, or even impractical in many circumstances. The outcomes of a predictive learner can be compromised when there is a discrepancy in data distribution flanked by the training data and test data. [7] Deep learning has been widely used in picture recognition recently, as a result of developments in artificial intelligence and computer vision technologies. Due to the significant quantity of data needed to train the network, deep learning also has several disadvantages. Performance suffers when there are insufficient photos in an available dataset [8]. One method at this point that minimizes effort is the use of transfer learning, which ensures accurate categorization with fewer training samples[9]. Transfer learning seeks to raise the performance of learners in the dedicated area by relocating statistics from multiple but related areas. Figure 1 illustrates the transfer of the learning process.

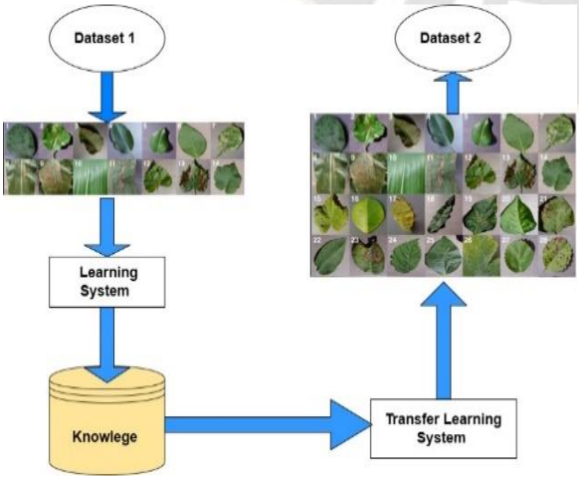


Figure 1: Transfer Learning

Transfer learning enhances learning by transferring knowledge from a previously acquired, analogous task to the new one at hand. Transfer learning is a method for using the skills learned when doing training for one kind of problem to undertake training for other similar problems or domains. Transfer learning is an idea that has its roots in educational psychology. Learning to transfer is the idea of generalizing experience, according to C.H. Judd's general theory of psychology[10].

Two learning activities must connect. To drive other two-wheeled vehicles more effectively, you should become proficient at cycling. Similar to autonomous automobile driving, an automated vehicle driving model can be used to accomplish autonomous truck driving. Using CNNs(Convolutional neural networks) that have been trained for one task as the basis for a model for another is a machine-learning technique called transfer learning. With large labelled datasets, such as public image collections, etc. Instead of beginning from scratch and resetting the weights arbitrarily, we can set the weights using a pre-trained network [11]. Reduced training time, generalization error, and processing costs are advantages of applying transfer learning while creating DL models [8].

CNN is a subtype of a deep learning network, that employs a sequence of convolution, pooling, and rectified linear unit (ReLU) layers that feed into a fully connected layer to recognize the connections and features in images. A CNN is fabricated of two hidden layers, an input layer, and an output layer. Typically, normalization, convolutional, pooling, fully connected, and layers make up a CNN's hidden layers (ReLU). This layer incorporates the different features that the earlier levels have uncovered[9], [10].

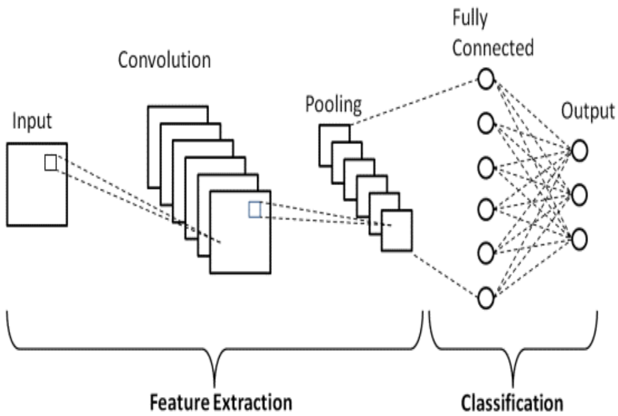


Figure 2: Typical CNN architecture

. ReLU can alternatively be referred to as an activation layer or a normalization layer. Equations are used to define the non-saturating, non-linear function. The activation layer or normalizing layer is another name for ReLU [14].

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The pooling layer, which is sandwiched amid the convolutional and fully connected layers, samples the desired image to avoid overfitting issues. To prevent overfitting issues, the input image is downscaled by the pooling layer, which is sandwiched between the convolutional and fully connected layers. The outcome of the layer above is connected to the layers below by FC layers. It is located in the CNN architecture's bottom layer and is coupled to the soft-max layer directly[15]. All of the preceding layers either directly or through activation processes provide input to the neurons in the FC layer. With the characteristics gathered from the previous layers, the Soft-max function is typically used to do class prediction [16]. Figure 2 depicts the typical CNN organizational structure.

## III COMPUTATIONAL PROCEDURE OF PLANT DISEASE DETECTION

The following presentation uses niceties to present the whole procedural paradigm for plant disease diagnosis using CNN. Figure 3 shows the steps involved in the working process of the model. The deep CNN model commences with training images, then moves on to preprocessing, applying augmentation, using previously trained models like Alexnet, Densenet, ResNet50, etc., and optimizing model parameters. Then tests are run, followed by a thorough examination of the data.

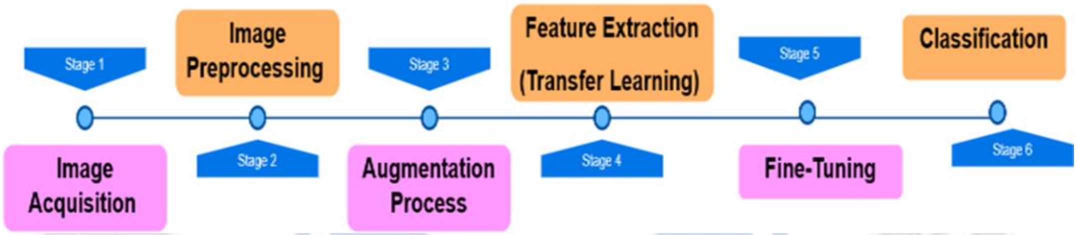


Figure 1 Computation Procedure of Plant disease Detection using Transfer Learning

*A. Image acquisition/Collection*

To prepare the labelled datasets (source datasets) for analysis, we must first create the images taken from the Internet or taken by digital cameras and UAVs are included in the labelled dataset from the cultivated field Different classifications of photos are represented from the data sources. The UAV and digital camera images are impacted by several unfavourable factors, such as diverse lighting and reflection conditions, object size and positioning, leaf movement, occlusion, background fluctuations, and phenological stages[17]. These differences in actual field circumstances help the system function in a genuine setting.

*B. Image Processing*

Before training a deep learning model, image processing is used to boost the quality of the dataset. Image Transformations are optimized to enhance the dataset's amount of images and condense overfitting by including a small number of deformed images with the training data. [18] . The user requirements determine how the collected photographs are resized, thus the initial phase is to choose the standard dimensions of images that can be utilized for research. Organizing the photos into groups based on the disease that is present in the leaf is the next step. The most crucial action that must be taken with images is pre-processing to obtain the necessary data free of undesirable distortions and highlight the aspects of the image that will be crucial for further processing [16].

*C Augmentation Process*

Several data transformation techniques are being used in data augmentation strategies to create new images for the current dataset. The training dataset's image count is increased by the use of this procedure. It aids in preventing the issue of overfitting during the training procedure[20]. post-image processing Numerous augmentation methods, including rotation, zoom, vertical shift, and shear range, are used. Image overturning, gamma correction, noise injection, horizontal shift, PCA colour augmentation, rotation, and scale adjustments are used to create improved images for the training data.

Ref [19] Separate the augmentation issue into two pieces. 1) Geometric techniques: rotating, flipping, and cropping 2) image metric techniques: edge enhancement, Color jittering, and fancy PCA. Popular data augmentation methods include deep convolutional generative adversarial network (DCGAN), basic image manipulation (BIM) and neural style transfer (NST)[21]. The most widely used BIM techniques include affine scaling, rotation, transformation, flipping, padding, cropping, and translation. An unsupervised neural network called the DCGAN uses training data to generate a fresh set of realistic images. [22]. Using reference photos for content and style, the NST is a method for transforming images [20].

*D. Feature Extraction(Pre-trained model/Transfer learning):*

Numerous plant sources could be employed as feature fundamentals for an AI-based model. However attributes

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connected to components like leaves are seen to be more substantial for the task, partly because they are easier to acquire than other parts like flowers, leaves, stems, etc[24]. Deep feature extraction is carried out based on the features extracted from a pre-trained CNN and deep feature extraction is performed. If complicated data has a lot of variables, feature extraction makes sense. The two most widely utilized deep learning transfer learning approaches are fine-tuning and deep feature extraction. The pre-trained network receives the input data for deep feature extraction, which stores and uses the stimulation values of multiple layers as features[25].

In a DL pipeline, feature extraction is incorporated into the learning process, where features are pulled out entirely automatically and without the assistance of a human expert. Using CNN as an example, computer vision experts can extract features automatically. A deep neural network that has been fine-tuned is trained for a job that is similar but where labelling is moderately easy. While the initial layers of the pre-trained the network can be static, the last layers of the model can be fine-tuned to acquire the characteristics of the fresh dataset.

TABLE 1:DETAILS OF PRE-PLANNED MODELS

| Pre-Trained model | Year | Model details | **Number of Layers** | **Types of CNN** |
|---|---|---|---|---|
| Alexnet | 2012 | Deep feature extraction uses features extracted from a pre-trained CNN as its Foundation. ReLU is placed after each convolutional layer and is used to "activate" the convolutional layer outputs. | 8-layer CNN (61 million parameters) | Spatial Exploitation based CNNs |
| VGGNet | 2014 | By utilizing small convolution filters and more convolutional layers, the network may be made deeper (3 *3). | 138 million parameters w | Spatial Exploitation based CNNs |
| GoogLeNet & Inception | 2014 | It's made up of layers of mlpconv. It substitutes a broad nonlinear function approximation for convolution filters. | **22 layers** | Spatial Exploitation based CNNs |
| ResNet | 2016 | a residual network is known as ResNet, which had 152 layers and was eight times deeper than VGG Nets. | 34 layers | Depth based CNNs |
| DenseNet: | 2017 | The DenseNet may provide L(L+1)/2 connections as opposed to the L connections of conventional convolution networks by using the feature maps from all preceding layers as inputs. | **100 layers** | Multipath based |
| MobileNets: | 2017 | two straightforward global hyperparameters that effectively balance latency. | 27 Convolutions **layers** | Multipath based |
| EfficientNet: | 2019 | EfficientNet-B7 uses a lot fewer parameters to obtain the best accuracy possible on ImageNet and three other transfer learning datasets, 84.4% top-1 and 97.1% top-5. | 237 Layers | Depth based CNNs |
| RegNet: | 2022 | Due to its simplicity and speed, the RegNet design space can operate flawlessly under a variety of flop regimes. Under equal training settings and flops, the RegNet model outperforms the well-known EfficientNet model, which is up to five times faster on the GPU. | | Multipath based |
| Inception V4 | 2016 | An inception layer performs everything and provides a concatenated output rather than requiring the convolution layer to choose between convolution and a pooling layer or from a variety of filter sizes and dimensions. | | Depth based CNNs |

The previously trained model is retrained using the new, short dataset, and the model's weight values are changed following the new task. The robust feature extraction and information mining capabilities of convolutional neural networks (CNN) have drawn significant attention[26]. Due to its effective feature extraction and learning process, CNN has been applied to an extensive series of tasks, including object recognition, semantic segmentation, image super-resolution, etc. While maintaining the standard learning topology, various CNN designs were presented to improve the concert of the corresponding systems. The well-known CNN architectures for object identification tasks among them include AlexNet, GoogLeNet, Inception V3, VGG16, Inception V4, DenseNets

, Resnet, and VGG. It entails representing images from new datasets consuming the properties of a pre-trained network.

The varied Semantics of various CNN Pre-trained modes are shown in Figure 4. One of the main benefits of models and methods that have been developed in these areas is that they can

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accomplish feature extraction without using segmented methods. As a result, using these techniques and models for practical purposes is simple. Deep feature extraction uses learned features from a trained convolutional neural network. Fine-Tuning A function's efficiency can be improved through fine-tuning. It makes little adjustments to enhance the result. Even a little change to the adjustment procedure can significantly affect how long computations take, how rapidly convergence occurs and the number of processing units needed for training. When the target dataset is enormous, fine-tuning the pre-trained network is important. It involves unfreezing a portion of a frozen model's top layer that is cast off for feature extraction.

Additionally, because the parameters of all layers excluding the final one are set using the pre-trained network, training will be finished quicker than it would have been with random initialization. Table 1 shows the variance semantics, the Number of layers and types of CNN for various pre-trained models of CNN.Based on the categorization we can divide CNN into 3 parts Spatial Exploitation, Multipath and Depath-based CNN.

Researchers employed spatial filters in the early 2000s to improve performance. It was discovered that a spatial filter and network learning go hand in hand[29]. GG and Inception outperformed all other networks in depth-based testing, which is a criterion that regulates how well networks can learn, according to ref [30]. Pre-trained Model Analytically, paths can connect from one layer to another while avoiding some intermediate levels. while extending the gradient to lower layers, these pathways address the issue of disappearing gradients.

D. Classification (Evaluation model):

Pre-trained models and feature extraction made up a training network. Pre-trained models are those that have already undergone training on huge datasets like ImageNet [27]. The third component's feature extraction for any image was done using this section. Currently, a network has acquired knowledge. The former step is to recognize the disease that is present in the input image: It is referred to as a cataloguing input image.

## IV LITERATURE REVIEW AND COMPARATIVE ANALYSIS

Numerous novel studies in the detection of leaf disease linked to transfer learning have been implemented as a result of the rapid development of data science, machine learning, and deep learning in recent years. In this section's Table 2, the analysis of the pre-trained, classification modelling, and measure parameter literature is shown. Table 2 presents and explains all the information required to assist readers in selecting one or more criteria and quickly comparing pre-trained deep learning models with different classification learning models.

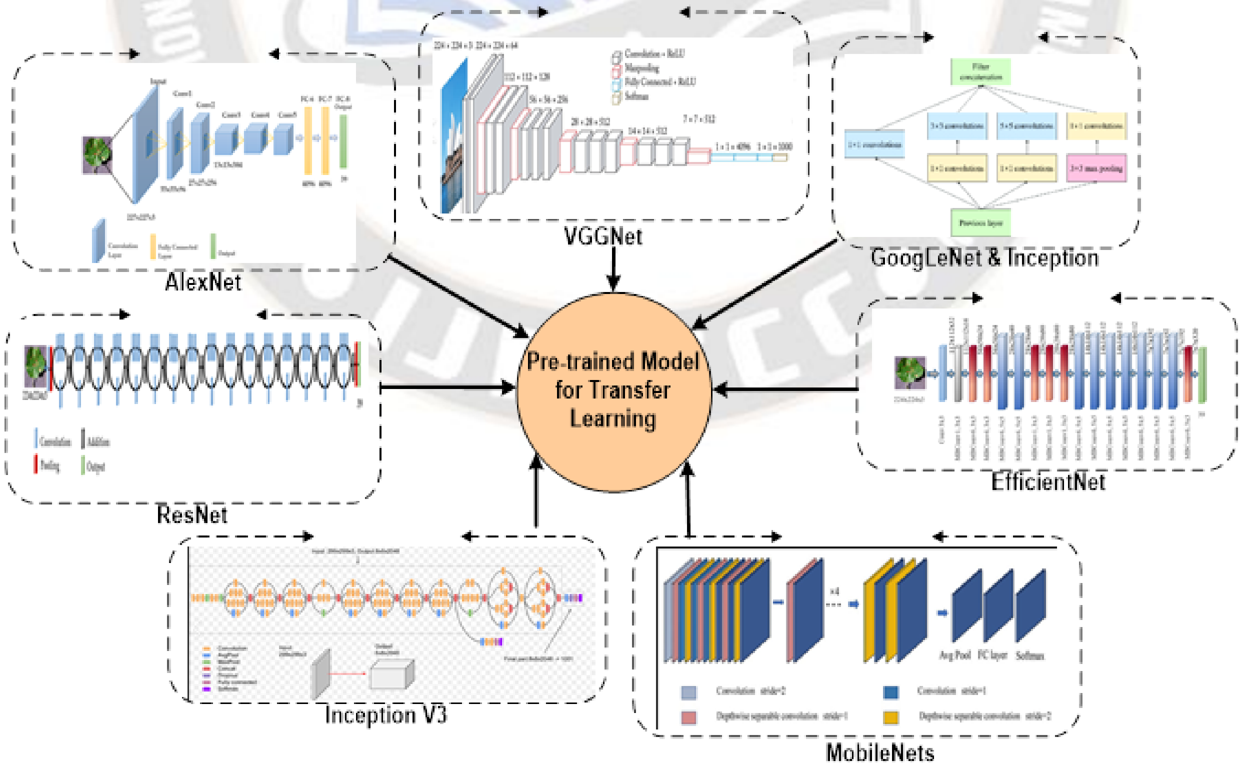


Figure 4 : Pre-trained Model of Transsfer Learning

TABLE 2: TABLE OF COMPARATIVE ANALYSIS

| Ref. | Pre-trained model | Classification model | Dataset | Plant | Disease | Accuracy |
|---|---|---|---|---|---|---|
| [30] | MobileNet-V2 | classification activation map (CAM) | ImageNet | Plant village | Apple scab, Black rot, etc | public dataset :99.85% multiple classes and complex background: 99.11% |
| [31] | AlexNet and ResNet101 | Least squared support vector machine (LS-SVM) | plant village dataset | Grape leaves | Leaf Blight black measles, Black rot | 99% |
| [24] | VGG16, VGG19, Inception-v3, and ResNet50 | Fine-tuning VGG16, | PlantVillage | Different species of plants | Black rot Leaf Blight etc | VGG16 – 90.40% |
| [32] | AlexNet, ResNet, GoogLeNet and VGGNet | CNN Model | National Bureau of Agricultural Insect Resources (NBAIR) dataset | Different species of plants | - | 97.47, |
| [24] | CONvnet | SVM and Adaboost | FLAVIA leaf image dataset | different species of plants | -- | 95.85% |
| [33] | AlexNet, GoogleNet and DenseNet201, Multi-model LSTM-based, | SVM and LSTM | Gathered in the cities of Malatya and Bingol | Apple | apple disease and pests detection | 99.2 |
| [34] | CNN | LVQ (Learning Vector Quantization) | Internet | Different species of plants | Leaf spot, bacterial spot, late blight, yellow curved leaf Septoria, | - |
| [35] | EfficientNet | CNN Model | PlantVillage dataset | different species of plants | powdery mildew, rust, black measles, late blight | 99.97% |
| [16] | VGGNet pre-trained on ImageNet and Inception | CNN Model | Fujian Institute of Subtropical Botany | Rice, Maize | Rice White Tip Maize Gray Rice Leaf, Maize Eyespot Smut, Rice Leaf Scald, Rice Bacterial Leaf Streak, Leaf Spot, Maize Common Rust, | 91.83% |
| [36] | Inception v3 AlexNet ResNet-34 DenseNet-169 | CNN Model | PlantVillage dataset | Different species of plants | Apple Scab, Cherry Rot Corn Northern Leaf Blight, Grape Black Powdery Mildew, | inceptionV3 w 99.76%. |
| [37] | InceptionV3, VGG16, ResNet, SqueezeNet, and VGG19 | | paddycrop Mendeley and Kaggle | paddy crops | light. Blast, Brown Spot | 96.40% |

## V CONCLUSION

The highest levels of accuracy for plant leaf disease identification and crop management attained by contemporary transfer learning and its architectures have been addressed and studied in this paper. This article discusses the Computational Procedure of Plant Leaf Disease Detection in-depth, along with the datasets utilized, work environment, deep learning models, data pre-processing, data augmentation approaches, Pre-Trained Model, and Fine tuning. Different pre-training backbone models, augmentation techniques, and the use of realistic datasets have also been mentioned in the Literature review section. In this paper, we reviewed recent research initiatives concerning the application of Transfer learning methods in agriculture over the last few years. Based on our findings, deep learning surpasses other widely used image processing techniques., however, if certain additional parameters are taken into account, its performance can be significantly improved. Additionally, Transfer learning outperforms currently available, widely accepted image processing algorithms and offers a high level of accuracy. According to the review, AlexNet and ResNet101 and ResNet50, InceptionResNetV2, learning algorithms with accuracy performance measures had the best performance for plant disease detection automation systems, with average accuracy ratings of 99%, 99.80%, and 99.11% respectively.

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