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A Comprehensive Analysis Of Diverse Image Processing Techniques In Agriculture

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Abstract

Agriculture plays a crucial role in fostering sustainable growth through the integration of various technological advancements such as image processing, artificial intelligence, deep learning, and the Internet of Things (IoT). The global population is increasing on a daily basis. The increasing demand within the agriculture industry has necessitated the collective enhancement of plant cultivation and field productivity. This paper emphasizes the significance of effectively managing the crop during its initial growth phase as well as during the harvesting era. Image processing and artificial neural networks are employed as distinct methodologies for detecting illnesses on leaves. When capturing images using drones, the resulting images undergo a process of segmentation and transformation, resulting in the identification of three distinct vectors that represent diseases. These vectors include colour, texture, and morphology. This paper reviews on various disease classification strategies that can be utilized for the detection of plant diseases.

Keywords: CNN, PNN, ANN, SVM, KNN.

Introduction

Recently, there has been a surge of interest in the domain of deep learning. In computer vision tasks, the convolutional neural network, an artificial neural network variant, has emerged as the prevailing technique. Its effectiveness was demonstrated in the ImageNet Large Scale Visual Recognition Competition (ILSVRC) in 2012, where it achieved remarkable results in object recognition, is the deep learning model with the most well-known algorithm. CNN is widely regarded as the most extensively established algorithm within the wide variety of deep learning models. CNN has performed at an expert-level in many domains, and agriculture research is no exception. Hassan et al.,2021 has implemented CNN to identify and diagnose diseases in plants from their leaves [1]. Vaishnnave et al., 2019 has replaced the SVM classifier with KNN classification to classify groundnut diseases[2]. Rangarajan et al., 2020 classify the eggplant diseases using multi-class support vector machine (MSVM) which takes the images as input from VGG16 which act as a feature extractor[3]. Researchers in agriculture have become very interested in CNN's potential, and various research studies have already been published in areas like lesion detection [4], classification [1], segmentation [5], image reconstruction [6] and natural language processing [7]. This article focuses on the fundamental ideas of CNN and how they apply to different agricultural tasks. It also examines the difficulties and limitations of CNN and its future directions.

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Artificial Neural Networks (ANN)

The ANN is one of the better and more accurate classifiers, especially in terms of how well it works for accuracy. The reason is for this is that ANN is useful in solving non-linear problems, such as leaf pattern identification. However, prior studies has shown that a leaf with an oblong design may enhance the recognition error rate, probably due to its homogeneous structure [8]. ANN's basic structure is an interconnected network of nodes. As shown in Figure 1, the desired output is generated by numerous layers of nodes connected to each other.

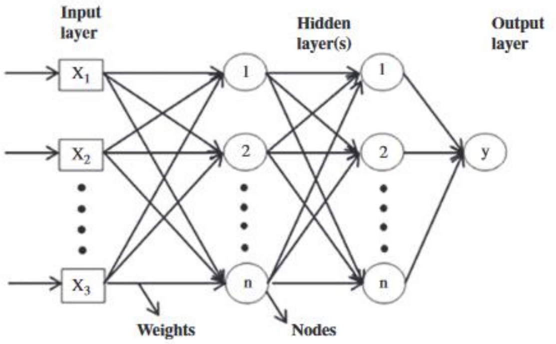

Figure 1: *Basic architecture of ANN (*[9]

Recurrent Neural Network (RNN)

Recurrent Neural Networks (RNNs) can be considered as the temporal extension of Artificial Neural Networks (ANNs). The primary purpose of these entities is to effectively handle and analyse sequential sets of information. Forecast models and language models rely on them as fundamental components. The two most prevalent types of recurrent layers in neural networks are GRU (Gated Recurrent Units) and LSTM (Long Short-Term Memory). These layers consist of cells that incorporate compact artificial neural networks, which determine the extent to which previous information should be propagated through the model. This is the manner in which the concept of "memory" was conceptualized. In the year 2017, Deng et al. introduced the concept of incorporating self-attention mechanism into RNN language modelling. They further utilized this model for sentence expression and observed favourable experimental outcomes [10]. Merity et al. 2017 employs the regularization technique and an optimization strategy to construct a language model utilizing LSTM, as stated in their research. The model utilizes word-level vectors as the input for feature representation in the modelling process, resulting in the optimal experimental outcome for word-level modelling tasks[11].

Support Vector Machine (SVM)

SVM is a supervised learning technique that is utilized for classifying data, performing regression analysis, and identifying outliers. SVM provides significantly higher accuracy than alternative classifiers such as decision trees and logistic regression. The kernel trick that it uses to handle nonlinear input spaces is one of the reasons it is so well-known. Zhang et al. has used of three kinds of multi-class SVMs from which Max-Wins-Voting SVM with Gaussian Redial Basis gives the best accuracy in classification of fruits [12]. Dino et al. has used has used three classifiers to classify the facial expression using SVM, KNN and MLP from which SVM gives the better results [13][14]. Vamsidhar, Rani, and Babu 2019 has used SVM to extract the features and ANN used for classify the plant leaf diseases[15].

Probabilistic Neural Networks (PNN)

The probabilistic neural network (PNN) is also a type of feed-forward neural network that effectively removes cyclic connections among its nodes. The architecture of PNN has shown in Figure 2. The PNN approach employs a Parzen window and a non-parametric function to estimate the parent probability distribution function (PDF) for each class. Subsequently, the application of Bayes' rule is employed to allocate the class exhibiting the greatest posterior probability to novel input data, while utilizing the probability density function (PDF) of each class to estimate the probability of the class for new input data. This methodology decreases the probability of misclassification. The Pattern Neural Network (PNN) is a widely employed tool utilized by machine learning engineers to perform tasks related to pattern detection and categorization. The classification problems are addressed by a Probabilistic Neural Network (PNN) through the utilization of either supervised or unsupervised statistical memory-based methods. Ashok et al., 2014 has used various feature extraction methods whose outcome is the input of PNN to automatically evaluate the quality of apples[16].

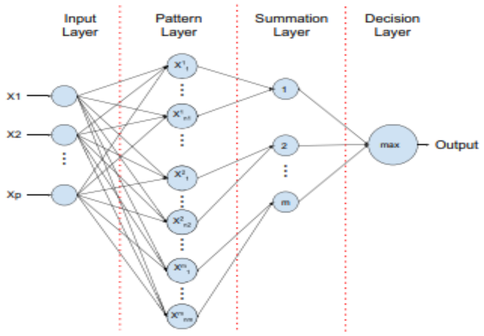

Figure 2: *PNN Architecture*[17]

K- nearest Neighbour (KNN)

Hossain et al., 2019 suggested a method for classifying and detecting plant leaf diseases using K-nearest neighbour (KNN) classifier. For classification, the leaf disease images textural features are retrieved[18]. The suggested method has a 96.76 percent accuracy rate for correctly identifying and diagnosing the diseases. Vaishnnave and Devi 2019 has worked focussed on distinguished between 4 different diseases of groundnut leaves[19]. Saputra et al. 2020 has worked on three diseases—Brown spot, Leaf smut and Bacterial leaf blight,—affect rice leaves, and the goal was to categorise images of these diseases[20]. The feature extraction for text analysis using the GLCM approach was suggested. The five feature values are entropy, contrast, correlation, energy, and homogeneity.

Multilayer Perceptron (MLP)

The Multilayer Perceptron (MLP) is also a type of supervised machine learning technique which falls within the category of feedforward artificial neural networks. The algorithm undergoes a training process using the available data to acquire knowledge and develop an understanding of a certain function. The system consists of three distinct layers, namely an input layer, an output layer, and a hidden layer, as depicted in Figure 3. The computational mechanism of the Multilayer Perceptron (MLP) primarily comprises an indeterminate number of hidden layers, which are positioned between the input and output layers. The flow of data within a Multi-Layer Perceptron (MLP) occurs in a unidirectional manner, moving from the input layer to the output layer. This process is analogous to that of a feedforward network. The MLP's neurons are trained to achieve optimal performance through the utilization of the back-propagation learning technique. To tackle problems that cannot be broken down into linear components, MLPs are trained to make approximations of arbitrary continuous functions. MLP's primary applications are in the areas of pattern recognition, prediction, approximation, and classification.

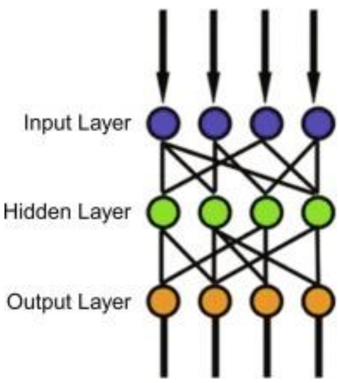

Figure 3*:Schematic representation of a MLP with single hidden layer.*[21]

Islam et al. 2014 categorised the level of the garbage bin, and an estimate of the volume of waste inside the bin was made using a Multi-Layer Perceptron (MLP) classifier[22]. Chatterjee et al., used SVM and MLP for classification of C3 and C4 electrodes for left- to right limb movements which gives satisfactory accuracy results that are 85 % and 85.71% respectively [23].

CNN

CNN is a form of deep learning model that is utilised for the purpose of processing data that exhibits a grid pattern, such as images. The creation of CNN was influenced by the organizational structure of the animal visual cortex [24],[25]. Its primary objective is to facilitate the automated and adaptive acquisition of spatial hierarchies of information, progressing from lower level to higher-level patterns. The three fundamental layers that constitute a standard CNN architecture are convolutional layers, pooling layers, and fully connected layers. The initial two layers, referred to as convolution and pooling layers, play an important role in the process of feature extraction. The final layer, referred to as a fully connected layer, has the responsibility for mapping the extracted features to the ultimate output, such as classification. To build CNN, you need a convolution layer, which is just a special kind of linear operation, and it's crucial to the algorithm’s overall performance and accuracy. Convolutional neural networks (CNNs) are highly efficient in image processing due to the fact that pixel values in digital images are stored in a two-dimensional (2D) grid, referred to as an array of numbers. Additionally, a kernel, which serves as an optimizable feature extractor, is applied at each position within the image. This phenomenon arises from the fact that a feature has the potential to present itself at any location within the image. The extracted features have the potential to evolve in a gradual and hierarchical manner, wherein each layer progressively enhances its output by feeding it into the subsequent layer. Training refers to the procedure of reducing the disparity between outputs and ground truth labels through the utilization of optimization techniques, including backpropagation and gradient descent, along other relevant methodologies. The process consists of improving various factors, such as kernels.

In majority of today's agricultural studies on disease, initial utilization of manually devised feature extraction techniques, such as texture analysis, is commonly observed. Subsequently, conventional machine learning classifiers, including ANN [26], KNN [27], Multilayer perceptron [28], and support vector machines [29], are employed.

Building blocks of CNN architecture

The architecture of CNN consists of a diverse range of construction components, encompassing convolution layers, pooling layers, and fully connected layers. A common architecture for a convolutional neural network includes many convolution layers, a subsequent pooling layer, and one or more fully connected layers. Forward propagation is the computational procedure by which input data undergo a series of transformations to produce corresponding output at various levels, as depicted in Figure 4.

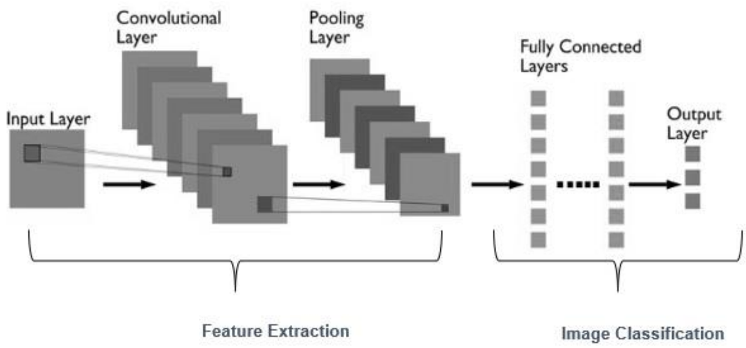

Figure 4: *Architecture of CNN*

a) Convolution layer

A crucial part of the CNN design, the convolution layer performs feature extraction, which often entails combining linear and nonlinear operations, such as the convolution operation and the activation function. These layers are composed of numerous filters, each of which has a width, height, and depth.

b) Pooling layer

In order to incorporate translation invariance for minor shifts and distortions, as well as reduce the number of learnable parameters, a pooling layer is utilized to perform a downsampling operation that decreases the inplane dimensionality of the feature maps. It is noteworthy that pooling layers do not possess any learnable parameters. However, the filter size, padding and stride are considered hyper-parameters in pooling operations, similar to convolution operations. A Max Pooling layer requires two arguments, kernel width and height, as well as a stride, as inputs. A feature map's top left corner is where the kernel begins, moving along the pixels to the right at the specified stride. The value for the relevant node in the pooling layer will be taken from the pixel with the greatest value present in the kernel window as shown in figure 5.

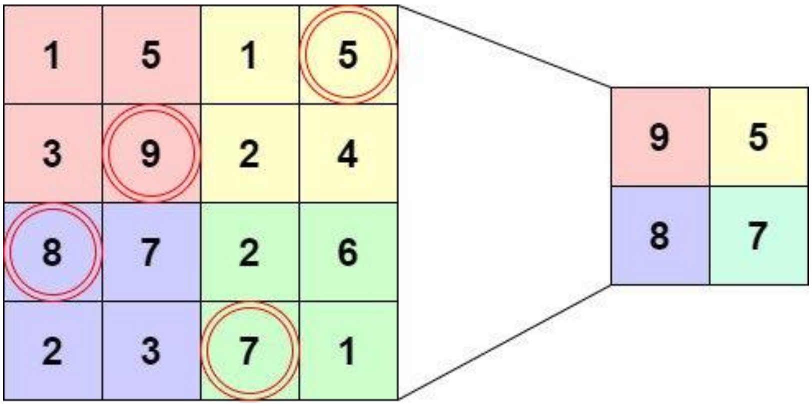

***Figure 5**: Max pooling process using a 2 × 2 filter.*

c) Fully Connected Layer

The fully connected layer encompasses the weights, biases and neurons serving the purpose of establishing connections between neurons across distinct levels. Typically, these levels are positioned prior to the output layer and constitute the final layers of the convolutional neural network architecture. In this process, the input image obtained from the preceding layers is transformed into a flattened representation and subsequently passed as input to the fully connected layer. The flattened vector subsequently undergoes additional fully connected layers, which typically involve mathematical function operations. At this juncture, the process of classification commences. The rationale for connecting two layers lies in the fact that the performance of two fully connected layers surpasses that of a single connected layer. The convolutional neural network employs layers that effectively diminish the level of human supervision required.

d) Dropout

In many cases, the connection of all features to the fully connected layer has been observed to potentially lead to overfitting in the training dataset. Overfitting is a phenomenon that arises when a certain model exhibits exceptional performance on the training data, leading to a detrimental effect on the model's performance when applied to new, unseen data. In order to address this issue, a dropout layer employed, whereby a subset of neurons is intentionally excluded from the neural network during the training phase, leading to a reduction in the overall size of the model. When a dropout rate is 0.3 is applied, it results in the random removal of 30% of the nodes inside the neural network.

The implementation of dropout in a machine learning model leads to enhanced performance by mitigating the issue of overfitting through the simplification of the network. During the training phase, neurons undergo a process of elimination from the neural networks.

e) Activation Function

The activation function is considered to be one of the most crucial elements in the CNN model. These models are employed to acquire knowledge and estimate intricate and continuous associations among the variables within the network. In normal terms, it determines which components of the model should be activated during the forward propagation process and which ones should be deactivated at the network conclusion. The inclusion of non-linearity introduces a non-linear component to the network. There exist a number of frequently employed activation functions in the field, including the Rectified Linear Unit (ReLU), SoftMax, hyperbolic tangent (tanH), and Sigmoid functions. Each of these functions possesses a distinct purpose or application. In the context of a binary classification Convolutional Neural Network (CNN) model, the sigmoid and SoftMax functions are commonly used. Conversely, in the case of multi-class classification, the SoftMax function is typically employed. Activation functions in a Convolutional Neural Network (CNN) model play a crucial role in determining the activation state of individual neurons, hence influencing the overall functioning of the network. The determination of the significance of input data for predictive purposes is contingent upon the use of mathematical processes.

Problems of CNN

Convolutional Neural Networks (CNNs) have demonstrated considerable potential in diverse computer vision tasks, such as the detection of agricultural diseases. However, the utilization of CNNs in this specific domain is accompanied by distinct challenges and limitations. Several challenges are associated with the application of Convolutional Neural Networks (CNNs) in the field of agriculture disease detection.

i. *Limited Data Availability:* Deep neural network training may be difficult due to the potential small size of agricultural datasets. Limited datasets have the potential to result in overfitting, a phenomenon in which the model exhibits high accuracy when trained on the available data but fails to effectively apply its learned patterns to novel, unseen data [26].
ii. *Class Imbalance:* In the field of agriculture, there exists a disparity in the occurrence rates of certain diseases, with some being relatively uncommon or infrequent when compared to the prevalence of healthy plants. A class imbalance may give rise to models that are biased in nature, giving precedence to the majority class rather than the minority class (such as in the case of disease detection)[27].
iii. *Environmental Variability:* Agricultural images frequently demonstrate considerable variability as a result of various factors, including lighting conditions, weather fluctuations, and camera configurations. Convolutional Neural Networks (CNNs) might encounter difficulties in generalizing across these variations, resulting in reduced performance in real-world scenarios[28].
iv. *Transferability Issues:* The efficacy of pre-trained convolutional neural network (CNN) models, which have been trained on general image datasets, may not be effectively transferred to agricultural images. The features acquired from generic images may not be optimal for identifying disease patterns in agricultural crops[29].
v. *Inter-Class Variability:* Diseases can emerge differently on plants, and symptoms can appear differently. These minute variations may be difficult for CNNs to pick up on, particularly in situations when there is a lot of intra-class variability[30].
vi. *Precision of Location:* Convolutional neural networks (CNNs) might encounter challenges when it comes to precisely determining the location of disease symptoms on plants. Accurate localization is of the utmost importance in order to comprehend the magnitude of an infection and develop targeted remedies[31].
vii. *Computational Resources:* The process of training and deploying deep convolutional neural networks (CNNs) can impose significant computational demands. In certain agricultural contexts, particularly within developing regions, there may be a deficiency of essential infrastructure and resources required for the implementation of advanced deep learning models[32].
viii. *Adaptability to New Diseases:* Convolutional Neural Networks (CNNs) are commonly engineered to cater to particular tasks, which can pose challenges when encountering novel diseases that have not been encountered before. The process of modifying pre-existing models to address emerging diseases may necessitate the acquisition of supplementary labelled data and the refinement of model parameters.
ix. *Data Annotation Challenges:* The process of generating precise and comprehensive annotations for agricultural datasets, particularly those pertaining to diseases, can be a laborious and costly endeavour. The training process may be impeded by a scarcity of annotated data.
x. *Explainability and Interpretability:* CNNs are frequently referred to as "black box" models, which means that it might be difficult to explain how they make certain judgments. This lack of transparency can be a limitation in agriculture, where interpretability is critical for decision-making.

The lack of large and varied insufficient datasets is the main issue with CNN-based DL's application in disease detection and classification in agriculture.

In order to tackle the difficulties related with the utilization of Convolutional Neural Networks for agricultural disease diagnosis, various strategies have been investigated by researchers and practitioners. The concerns described can potentially be addressed by the following solutions:

i. *Data Augmentation:* Expanding the existing dataset can be achieved by employing several approaches, including but not limited to rotation, scaling, flipping, and alterations in lighting conditions. These methods contribute to enhancing the effective size of the dataset. The implementation of this approach has the potential to mitigate overfitting and enhance the model's ability to generalize[33].

ii. *Transfer learning:* The utilization of pre-trained models on extensive and varied datasets, followed by fine-tuning specifically for agricultural disease detection tasks, can effectively mitigate the challenges posed by small dataset availability. Transfer learning enables the model to leverage the acquired information from different domains [34].

iii. *Domain-Specific Pre-training:* The use of convolutional neural networks for training on datasets that are primarily focused on agriculture or plant pathology has the potential to enhance the model's proficiency in identifying disease patterns that are distinct to crops[35].

iv. *Localization Techniques:* The integration of attention mechanisms or region-based convolutional neural networks (R-CNNs) has the potential to enhance the precision of illness symptom localization on plants, hence offering more comprehensive insights into the impacted regions[36].

v. *Class Imbalance Techniques:* Addressing class imbalance concerns can be achieved by the implementation of many procedures. These tactics include oversampling the minority class, under sampling the majority class, or utilizing more complex methods such as generating synthetic samples, as exemplified by the Synthetic Minority Over-sampling Technique (SMOTE) [37].

vi. *Ensemble Learning:* The integration of predictions derived from various Convolutional Neural Network (CNN) models has the potential to improve both robustness and overall performance of the system. The utilization of ensemble methods can effectively reduce the potential risks associated with depending solely on the biases and errors inherent in a single model[38].

vii. *Explainable AI Techniques*: The utilization of explainability approaches, such as Grad-CAM (Gradient-weighted Class Activation Mapping) or attention maps, can offer valuable insights into the specific areas within an image that significantly influence the decision-making process of a model. This incorporation of explainability techniques serves to enhance the interpretability of the model's outcomes[39].

viii. *Edge Computing:* The implementation of edge computing solutions facilitates the deployment of models directly on devices situated in the field, thereby diminishing dependency on extensive processing resources and enabling prompt identification of diseases in real-time[40].

ix. *Handling Environmental Variability:* The incorporation of a wide range of environmental conditions in the training dataset, coupled with the application of normalization techniques, can enhance the model's capacity to generalize effectively across varying lighting and weather situations[41].

x. *Continuous Model Update:* The implementation of methods for continuous model updates can facilitate the adaptation of Convolutional Neural Networks (CNNs) to emerging diseases. The regular updating of models with fresh data is crucial to maintain their relevance in dynamic agricultural situations[42].

xi. *Collaborative Efforts and Crowdsourcing:* Facilitating the engagement of individuals in collaborative endeavours and crowdsourcing initiatives can contribute to the generation of extensive and heterogeneous datasets. This can prove to be particularly advantageous in areas where there are limited resources available for data collection.

In the realm of agriculture, disease detection plays a crucial role in ensuring crop health and maximizing yields. By harnessing the potential of convolutional neural network (CNN) models and tailoring them to the specific challenges of agricultural disease detection, researchers aim to enhance the accuracy and feasibility of these solutions, paving the way for more efficient and sustainable farming practices.

Table 1: *Comparison of different plant disease detection techniques.*

Plant	Method	Accuracy	Reference
Fruits	SVM	88.2%	[12]
Apple	PNN	88.33%	[16]
Citrus	MLP	----	[44]
Citrus	CNN	94.16%	[45]
Tea Leaves	CNN	90.16 %	[43]
Plant leaves	KNN	96.76%	[18]
Rice leaves	GLCM and KNN	65.83%	[20]
Cucumber	Own CNN	93.4%	[46]
Grapes	AlexNet	97.62%	[47]
Tomato	ELM (Own classifier)	84.94%	[48]
Cashew	CNN	97.76%	[49]

The Convolutional Neural Network mimics how our visual systems perceive the environment. As soon as we see an image, we immediately divide it into several smaller sub-images and analyse each one independently. We combine these smaller images to analyse and understand the larger image. Chen, Liu, and Gao 2019 classify the tea leaf diseases using LeafNet CNN model gives the better accuracy against SVM and MLP algorithms. Table 1 shows the use of different techniques to classify the disease in agriculture field.

Conclusion

The systematic review findings highlight noteworthy developments in the application of deep learning (DL) for the detection and diagnosis the diseases of plants, requiring the focus of the research community. These emerging trends signify novel approaches and techniques that have the potential to significantly contribute to the field.

- The advantages of deep learning are evident as it eliminates the need for feature engineering. The reason for this is the ability of deep learning models to autonomously learn and identify significant features through the training process.
- The utilization of transfer learning has the potential to yield superior performance outcomes in comparison to the process of training a model from scratch. The utilization of a larger dataset, such as ImageNet, for pre-training the convolutional neural network (CNN) is recommended due to the limited size of the leaf disease dataset. Subsequently, refining the network using the dataset of leaf diseases will lead to improved accuracy in detecting leaf diseases.
- In order to enhance the model's ability to generalize effectively to novel images, particularly in real-world scenarios, it is imperative to employ larger datasets that exhibit a wide range of variations during the training process. The process of training in the field of computer neural networks (CNN) is known to be computationally demanding and necessitates the utilization of high-performance graphical processing units (GPUs).

In the future, it is anticipated that instructions will involve the integration of robots to automate the process of image acquisition. Subsequently, the augmentation of plant disease image datasets will be pursued by leveraging newly established models. These models will aim to is to provide descriptions of structures that are more efficient, with reduced parameter count. Additionally, new image upscaling techniques, such as Generative Adversarial Networks (GANs), will be employed.

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