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Survey of Accuracy Prediction on the PlantVillage Dataset using different ML techniques

Vaishnavi Pandey[1, *], Utkarsh Tripathi[2], Vimal Kumar Singh[3], Youvraj Singh Gaur[4] and Deepak Gupta[5]

[1, 2, 3, 4, 5] Pranveer Singh Institute of Technology, Kanpur

Abstract

A plant is susceptible to numerous illnesses while it is growing. The early detection of plant illnesses is one of the most serious problems in agriculture. Plant disease outbreaks may have a remarkable impact on crop yield, slowing the rate of the nation's economic growth. Early plant disease detection and treatment are possible using deep learning, computer-vision, and ML techniques. The methods used for the categorization of plant diseases even outperformed human performance and conventional image-processing-based methods. In this context, we review 48 works over the last five years that address problems with disease detection, dataset properties, the crops under study, and pathogens in various ways. The research results discussed in this paper, with a focus on work published between 2015 and 2023, demonstrate that among numerous techniques (MobileNetV2, K-Means+GLCM+SVM, Residual Teacher-Student CNN, SVM+K-Means+ANN, AlexNet, AlexNet with Learning from Scratch, AlexNet with Transfer Learning, VGG16, GoogleNet with Training from Scratch, GoogleNet with Transfer Learning) applied on the PlantVillage Dataset, the architecture AlexNet with Transfer Learning identified diseases with the highest accuracy.

Keywords: AlexNet, Transfer Learning, Deep-Learning, Plant Disease Detection, GoogleNet, RCNN

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*Corresponding author. Email: vaishnavipandey4648@gmail.com

1. Introduction

A sizable portion of the population in every nation, especially in rural areas, depends primarily on agriculture for their livelihood [1]. Plant diseases are the primary factors that obstruct the growth of the plant. Due to this obstruction, yield and quality significantly decrease, making a significant contribution to agriculture. Therefore, prior detection and treatment of plant disease can help preserve the entire crop. Agriculture has become more complex and specialized over the past few decades, with a focus on increasing yields, improving efficiency, and avoiding environmental impact. In general, all the countries in the world produce a vast range of crops as per their environmental conditions. These crops are then exported to different countries as per their demands. Therefore, it is essential to produce crops with the highest possible yield. The stems, roots, fruits, and leaves of the plants are the most likely areas where disease can occur and spread. For a disease, there may be a chance of different symptoms, causes, characteristics, and the impact of the climate on that location. According to studies, scientists believe that in the range of a minimum of 20% to a maximum of 40% of the worldwide annual crop yield is being lost due to a number of plant diseases [2]. The most important thing is to minimize the spread of disease, so the yield should be higher. which, in turn, meets the requirements of the country's increasing population. So, the most important thing is that early detection and prevention of diseases can save the crop's yield.

From the studies [2], it was also observed that the farmers of underdeveloped countries always tried to identify the diseases with their naked eyes, but it was too late to save the crop. Many farmers are still not able to identify the diseases because of a lack of knowledge about plant diseases. Pathogenic organisms, such as parasitic plants and insects, as well as fungi, bacteria, viruses, and protozoa, cause the principal infectious plant disease. These happen due to spontaneous changes in the climate [3]. To make the system faster, automatic techniques have been designed to swiftly and precisely identify and diagnose plant diseases. But this is extremely difficult, costly in nature, and imprecise. Techniques like image processing and computer vision are approachable areas through which recognition and classification of plant diseases can be done, which increases the viability of the cultivation yield. In the past several decades, numerous studies on image processing techniques using different deep-learning models on a variety of datasets, including various types of plants, have been carried out. A number of architectures for classification and segmentation, such as AlexNet, VGG16, InceptionV3, GoogLeNet, ResNet50, SegNet, U-Net, and R-CNN, have already been suggested for a variety of applications.

The remainder of the survey is formatted as below. The study that the researchers conducted was briefly covered in Section 2. Most of the work was done over the last five years. This demonstrates the utilization of artificial intelligence to identify plant illnesses. The outcome of this unit says a lot about the methodologies used in the research paper. These methodologies include the acquisition of images, different characteristics of the dataset, preprocessing techniques, augmentation of images, model architectures, parameters used in training, and different evaluation metrics, discussed in Section 3. Finally, the accuracy of various architectures on the plant village dataset is presented in the conclusion section.

2. Literature Review

In order to improve crop yield of crops, farmers use pesticides on plants to control diseases. This practice is not good for the health of the human body. This can be minimized with the help of early detection of the disease. To identify the diseases, a study on different diseases, their symptoms, and their prevention methods is needed. For this, knowledge of such diseases and their effects on different types of plants through images is required. The authors of [3] studied such images and proposed a remote sensing technology in real-time for the early detection of illnesses. A self-acquired dataset from controlled and wild environments was used. The accuracy attained was 94.54% from 15700 leaves from sick plants and 9800 leaves from plants that were growing well. Thus, these techniques proved to be effective for the cause. In the same domain, the authors of [4] studied the diseases and proposed a software method to automatically recognize and distinguish plant leaf diseases. Six classes of leaves and 10 texture features, each containing 32 samples of the sugar beet leaf data-set, were taken to train the model using the K-mean clustering technique. For recognizing plant ailments, the histogram comparison approach is applied. The created algorithm proved effective in accurately identifying and categorizing the studied disorders with a precision between 83% and 94%. Fungus and bacteria can cause a variety of plant diseases. To identify these diseases, Dhaygude and Kumbhar [5] proposed a processing strategy for the automatic early identification and detection of plant illnesses. The presented model was trained on over 3000 images of sugar beet, which were categorized into 6 classes. For feature extraction, picture pre-processing methods were used. A patch size of 32x32 was used, the segmentation of the pictures was carried out, and usable segments were produced. These segments are utilized in the color co-occurrence matrix for texture analysis. Identifying plant diseases with the help of direct visual methods is a tedious task. To minimize it, the researchers in [6] used a self-acquired dataset of 500 images and then classified diseases using genetic algorithms for image segmentation. In the same field, Mohanty et al. [7] used modern technology like smartphones and highly advanced cameras to collect 54306 pictures of the PlantVillage dataset of plant leaves with a distribution of 38 label categories. A CNN (Convolutional Neural Network) is claimed for the classification of 26 illnesses in 14 crop species. AlexNet and GoogleNet architectures were used with either learning from scratch or transfer learning mechanisms for the classification and detection of disease, with an accuracy of 85.53% and 99.34%, respectively.

In the segment on tomato diseases, the authors [8] used a collection of 87,848 pictures of 25 distinct plants in 58 various categories of Plant-disease and employed five architectures: AlexNet, AlexNetOWTBN, GoogleLeNet, Overfeat, and VGG. In the categorization of 17,548 unseen and fresh plant leaf images, VGG16 was seen to produce the most favorable result with a rate of 99.53%. For the Tomato Segment of Diseases, Qiufeng et al. of China [9] utilized tomato plant leaf samples from the Plant Village dataset, classifying tomato leaves into 6 different categories using AlexNet and VGG16. The study also showed that a decline in image quality results in a decline in prediction accuracy. In the tomato field, a lot of work was done. Scientists from China [10] used tomato leaf samples from the PlantVillage dataset. Then, by using deep convolutional GNNs, they diversified the dataset. Through this, they enhance the accuracy of the model. Yang et al. of China [11] used tomato leaf samples of the Plant Village dataset with four kinds of diseases. They extracted the features by using Fast-RCNN (proposed) and RPN methods. For deeper-level classification, they used ResNet while using the Skip-Connection identity mapping technique to direct input layers to many layers. They use intermediate features and cross-layer operations to improve the current clustering results. To improve the results of clustering in their study, they used K-means clustering. The dataset of 3000 images of tomato plant leaves that Naresh et al. [18] used was resized to 256 x 256 pixels and rendered in grayscale. Prior to segmenting the targeted area from the original images, the input photos underwent preprocessing. The photos are then further processed using different CNN model hyperparameters. Arranged tomato leaves according to their type and marked with the correct acronym were fed to CNN, which obtained an accuracy of 98.49%. The goal is to evaluate the effectiveness of U-Net and Modified U-Net in image segmentation, Srdjan et al. [20] used 18,161 tomato leaf images from dataset of the Plant Village accompanied by corresponding segmented leaf masks. The EfficientNet architecture is then utilized for classification. From the PlantVillage dataset, Harakannanavar et. al. [22] used samples of tomato leaves. To predict the illness at an early stage after improving the image quality using histogram equalization techniques, the authors [22] used contour tracing and K-means clustering. By using this approach, the model's performance is increased. In continuation with the above research on tomato plants, Ahmed et al. [24] also used tomato leaves from the most well-known Plant Village Dataset, vegetative leaf specimens. The quality of images is enhanced with histogram equalization. They used nine pre-trained architectures, such as EfficientNet-B0, MobileNet, MobileNetV2, DenseNet121, DenseNet212, ResNet50, NasNet-Mobile, ResNet152V2, and VGG16, to train the data set using transfer learning. The observation said that MobileNet-V2 is more efficient. due to its accuracy. In the research work [25], the scientists work on tomato plant dataset samples from the Plant Village Dataset. They scaled the images between 0 to 1 and CNN, with six layers used for the classification. Batch normalization is used after each convolution. 32 filters were used for the convolution with the ReLu activation function. The model, which made use of a ten-node layer of softmax and sigmoid, predicted ten different classes of tomato plants. Their findings surpass those of cutting-edge deep neural network techniques that use the PlantVillage database, while the suggested solution uses the least expensive architecture.

To avoid the food problem in China, the researchers [12] tried to yield more crops on small pieces of land. The evidence suggests that early disease detection helps reduce plant diseases. In their studies, they introduced the Inception network with a residual unit to create a hybrid network called: Inception-ResNet-V2. It contained cross-layer, multi-way convolution, direct edges, and, as the activation function, ReLu. It used transfer learning to improve model accuracy, convergence speed, and approximation accuracy. A residual unit is also included to address gradient disappearance and explosions. The Indian economy is majorly supported by farming. In India, more than seventy percent of people are dependent on agriculture. Suresh et al. [13] used a heterogeneous range of images with the plant village dataset throughout the training phase and used neural networks for the purpose. Their main aim is to identify the lighting and background noise difficulties in the dataset as compared to the actual application. The potato is the most consumable vegetable in India, contributing 28.9% of the total agricultural product in India and 4th in the world market. In order to identify diseases on potato farms more quickly, researchers [14] developed an automated system on VGG 19 architecture with the help of transfer learning mechanisms. For this process, they took the data from Plant Village and the ImageNet Dataset. The authors [15] combined the idea of smart farming with machine learning and IoT devices to diagnose plant disease using images. İmbalanced data in a dataset creates the biggest problem for achieving accuracy through machine learning. To handle this, the author [16] proposed a model with three configurations. With the help of this model, a user can analyze the accuracy of a single class. The authors [17] used SVM classification with deep learning algorithms with thirty-six number of attributes on 683 instances for identifying the diseases of Soya Bean with 19 classes. On the low-dimension representation of images, it is very difficult to identify plant diseases. To achieve the accuracy the scientist [19] developed a hybrid model with Convolutional Auto-encoder Network and CNN. These attained a training accuracy of 99.35% as well as a testing accuracy of 98.38% with just 9,914 training parameters. To make the farmers of India aware of the current edge-cutting smart technologies Sunil et. al. [21] put forth a detection mechanism to recognize the disease on the basis of plant leaves with the help of methods of computer vision and ML approaches. In terms of green cardamom production, India ranks among the top nations. In the field of allopathy and ayurveda, green cardamom is used as a flavor agent. To diagnosis the disease in such high priced exotic plant Sunil et. al. [23] proposed EfficientNetV2 CNN model. The approached reached to the accuracy 98.26%. Pandian et al. [26] proposed a five layered deep CNN model for identification of leaf diseases. They also use image augmentation used to avoid underfitting of the available dataset. The overall performance of the suggested DCNN model is 98.41%. Kundu et. al. [27] used the Maize Net deep learning model for identification of plant diseases, the prediction of severity, and the loss estimation of crops. They also developed a web application named "Maize-Disease-Detector" and integrated the model. Dual visible light cams (left as well as right) or a thermal imaging device and stereo visible light images were obtained. Bringing these three types of photos into the mix can increase the precision of identifying healthy as well as diseased plant images. This technique does binary classification , which is either healthy or diseased, using a support vector machine. The scientist [28] uses the concept of thermal image capturing technique with ML for classifying the plants as well as the agricultural diseases. the proposed methods reach the accuracy to 98.55%.

Plant illnesses exert an adverse impact on farmers with tiny plots of land whose livelihood is contingent upon the crop production. Umamaheswari et. al [31] suggested an even more effective and real-time technique that made use of pipelined approaches on the Kaggle Leaf Dataset. This approach was used for feature extraction, classification, significant spots and infection segmentation. It was noted that the LSTM model had the ability to effectively recognize broad types of leaf illnesses in real-time, along with effective treatments. As farming is a field that applies Machine Learning actively, Shah et.al [32] proposed the architecture of Teacher/Student residual architecture for categorization and visualization. Plant illnesses, changes in the climate and rapid loss of pollinators are among the factors that are responsible for food scarcity. Anwarul et. al. [33] presented a web application to provide ease in uploading images for identification. The model was based on CNN with seven convolutional layers on the Plant Village dataset of plants namely potatoes, bell peppers and tomatoes. Modern agriculture practices strive to spot ailments early on, which generally requires a lot of computation in machine-learning algorithms, Bensaadi et. al. [34] suggested a low-complexity CNN. Still, with reduced complexity, the proposed method achieved 97.04% accuracy. Along with disease detection, pests and the growth of unwanted plants like weeds around the crops is also a major issue regarding proper crop production. To tackle this scenario, Meena et. al. [35] observed that among various popular machine learning algorithms, DenseNet attended the optimum accuracy for three primary concerns, at 99.62%. Tea is a major export product of India, which is why illnesses in the leaves of tea plants put forth a significant loss. This is the reason for the high importance of early detection and prevention of plant diseases in tea. Datta et. al. [36] used Deep CNN on the Tea Leaf Dataset for the classification of its diseases. The model identified chronic tea leaf ailment with 95.56% accuracy. The diseases included were Algal Spot, Brown Blight, and Grey Blight. For precision farming, it is essential to single out illnesses at the early signs. Falaschetti et. al. [37] used ESCA and Augmented Plant Village dataset in the study. They performed real-time classification by implementing low-power OpenMV camH7 Plus with the help of CNN under a resource-constrained environment. This method achieved 98.10% accuracy.

The above discussed research says that most of the research is done on publicly available dataset. Some research is done on the own generated dataset. It was also observed that a number of works is done on crops like potatoes and tomatoes. Some of the work was done on vegetable plants. However, it was observed that a numerous number of methods are required for creation and correction of data. These methodologies are discussed in the next section.

3. Methodology

The Plant Ailment Detection System strives to make it simple and quick for farmers to determine which illnesses their plants may have. The Mohanty [7] dataset from the Epidemiology Lab at the EPFL in Geneva is used in this study for diagnosing ailments in plants via validation and training.

3.1. Image Acquisition

The following list of image acquisition methods includes those that various authors have used.

Table 1. Image Acquisition Techniques

Reference	Technique	Description
[39]	*Digital Imaging*	capturing images using digital cameras, scanners, or other digital imaging devices.
[40]	*Analog Imaging*	capturing images using traditional film cameras or other analog imaging devices.
[41]	*Medical Imaging*	using various imaging techniques like ultrasound, PET scans, CT scans, MRI, X-rays and others to diagnose and treat medical conditions.
[42]	*Remote Sensing*	using imaging technologies to collect data from a distance, such as satellite or aerial photography.
[43]	*Industrial Imaging*	using imaging technologies to inspect and analyze industrial products and processes, such as machine vision systems in manufacturing.
[44]	*Microscopy*	using imaging technologies to visualize objects or structures at the micro or nanoscale, such as electron microscopy or confocal microscopy.
[45]	*Computational Imaging*	using mathematical models and algorithms to enhance the quality or efficiency of digital image acquisition, such as compressive sensing or super-resolution imaging.
[3]	*Thermal Imaging*	using infrared cameras to capture the infrared radiation emitted by objects and convert it to visualize heat patterns.
[3]	*Fluorescence Imaging*	using fluorescent molecules that produce images of biological structures and processes, it enables the visualization of specific molecules and cellular structures with high sensitivity and resolution.

From the above discussion, the most popular technique of data collection is digital imaging [51]. The pictorial presentation of these methods is given in Figure 1.

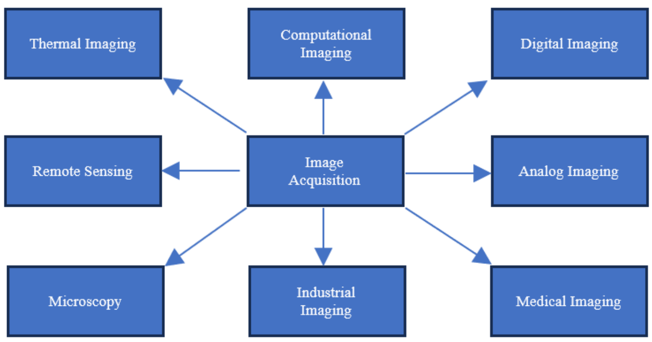

Figure 1. Image Acquisition Techniques

3.2. Dataset Characteristics

A dataset is an assortment of formatted data. Generally, it is stored in a database or in a computer file. The characteristics of data might differ depending on the variety of data contained, the purpose of the dataset, and the data collection techniques utilized. Some common characteristics are:

Table 2. Data Characteristics

Reference	Characteristics	Description
[46]	*Size*	Dataset's total record count.
[47]	*Dimensionality*	Dataset's total features and variables count.
[48]	*Sparsity*	The proportion of missing or incomplete data in the dataset. This can affect the accuracy and performance of the computations or analysis performed using the dataset.
[49]	*Noise*	The presence of random or unnecessary data within the dataset. This affects the reliability, as well as robustness, of the analysis.
[50]	*Diversity*	The distribution and range of values, categories, or types of data in the dataset. This can affect the compatibility of various statistical or machine-learning techniques.
[51]	*Bias*	The systematic distortion, or imbalance, in the dataset. This can affect the validity and generalization of the analysis.
[52]	*Privacy and Security*	The sensitivity and confidentiality of the data in the dataset. This is a major requirement to protect the privacy and security of individuals or organizations represented by the dataset. It can be done by taking special precautions for the same.
[53]	*Format*	The organization and structure of the dataset. It varies based on the software, platform or protocols used to collect, store and share data.
[54]	*Granularity*	The level of detail or resolution of the data. This can affect the relevance and specificity of the analysis.
[55]	*Temporality*	The time dimension of the data. This affects the analysis and interpretation of trends, patterns and connections.
[56]	*Source*	The origin, credibility and provenance of the data. This can affect the reliability and quality of the analysis.
[57]	*Context*	The background and environmental factors that influence the data. This can affect the interpretation and generalization of the analysis.
[58]	*Representative-ness*	The extent to which the dataset reflects the population or phenomenon of interest. This can affect the validity and generalizability of the analysis.
[59]	*Accessibility*	The ease and availability of accessing and using the data. This can affect the efficiency and effectiveness of the analysis.
[60]	*Complexity*	The degree of complexity or interdependence of the data. This can affect the suitability and feasibility of different analytical approaches.

These are the essential characteristics for understanding the format and the preprocessing techniques with respect to the dataset being used.

3.3. Data Pre-processing

Data preparation is a significant stage in the area of machine learning. In data preparation, to structure the data into a usable format for analysis, the data is cleaned and transformed. The process of transforming unprocessed data into a structure appropriate for analysis is referred to as data preparation. Some techniques of data preparation strategies are:

Table 3. Data Preparation Strategy

Reference	Techniques	Description
[61]	*Define the problem, and the goal*	Firstly, define the problem that is to be solved. Also, define the goals to be achieved from the analysis of data. This helps determine which data is relevant

		and what types of pre-processing steps are required.
[62]	*Data cleaning*	Data cleaning involves the identification, correction, and removal of errors, duplicates, missing data, and other inconsistencies present within the data set. For the maintenance of the quality and thoroughness of the analysis, this step is vital.
[63]	*Data integration*	While working with multiple datasets, it might be required to integrate those into a single dataset before analysis. This involves the identification of common variables to combine the data and resolve any discrepancies or inconsistencies.
[63]	*Data reduction*	Data reduction involves reducing the dataset size by eliminating redundant or irrelevant data points features, or by sampling a subset of the data. This can help speed up analysis and reduce storage requirements.
[61]	*Data splitting*	Dividing a dataset into Training, Testing and Validation datasets is called Data Splitting. This is a necessary step that guarantees that the model doesn't overfit the training dataset and generalizes effectively to new data.
[64]	*Documentation*	It is essential to document data preprocessing steps. It is to make it easier for others to replicate the analysis and understand the decisions made during the process.
[63]	*Handling missing values*	In addition to identifying missing values, it is also necessary to decide how to handle them. Common strategies include: a. Imputation- lining up missing values by using estimations derived from other available data. b. Deletion- eliminating rows or columns from the dataset that contain missing values. c. treating missing values as a separate category.
[65]	*Outlier detection*	These are data points that deviate notably from the typical values of the dataset. Detecting and handling outliers, which can be important for accurate analysis. Common techniques include: visual inspection, statistical tests, and machine learning algorithms.
[66]	*Encoding categorical data*	If the dataset contains categorical data, data that fall into discrete categories such as color or location, then it needs to be encoded numerically so that it can be used in ML models. One-hot encoding, label encoding, and binary encoding are few common techniques to implement Encoding.
[63]	*Data Discretization*	This technique involves converting continuous data into discrete data by dividing the data into intervals or bins. This is useful when analyzing data that has a large range of values.
[63]	*Data Normalization*	This technique involves transforming the data so that it has a standard scale or distribution. This can be done by rescaling the data or using techniques like Z-score or min-max normalizations.
[63]	*Feature scaling*	When working with machine learning algorithms that use distance-based metrics, it is important to scale features so that they have similar ranges.
[63]	*Dimensionality reduction*	When working with high-dimensional data, it can be useful to decrease the number of areas of interest to improve model performance and reduce overfitting. Common techniques include: a. Principal-component analysis (PCA) b. Linear-discriminant analysis (LDA) c. T-distributed stochastic neighbour embedding (t-SNE)

As the characteristics and variety increase, the preprocessing or preparations required change for the best results from the dataset. Such analysis and processing have an impact on the contextual information obtained from the data [63]. The compiled data preprocessing methods are shown in Figure 2.

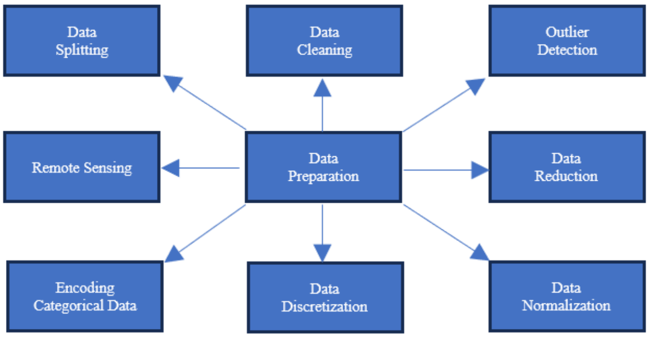

Figure 2. Dataset Preparation Strategy/ Data Pre-Processing

3.4. Data Augmentation

In machine learning, the preciseness of the training data is essential for performance of the model. However, in many cases, obtaining large and diverse datasets can be challenging and expensive. Data augmentation proves itself an effective technique to address this issue by generating fresh data from the existing dataset, adding artificial data points that are similar to the original data. The purpose of data augmentation is to enhance the performance of ML models by providing them with more diverse and representative data.

Data augmentation has been shown to have significant consequences on image classification model performance. By increasing the size and diversity of the dataset, augmentation aids the model's universality to be better to fresh examples. In a study conducted on the CIFAR-10 dataset, it was found that using data augmentation techniques improved the classification and model accuracy from 74.8% to 86.1%. Similarly, in a study conducted on the ImageNet dataset, it was found that using data augmentation techniques improved the top-1 classification accuracy of the model from 71.5% to 74.8%.
Following are some typical methods for data augmentation:

Table 4. Data Augmentation Techniques

Reference	Techniques	Description
[67]	*Flipping*	The original photos are rotated either horizontally or vertically in this process. For tasks involving image classification, this is especially helpful. This augmentation is among the simplest to put into practise and has shown promise on datasets like CIFAR-10 and ImageNet.
[68]	*Cropping*	In this technique, a random crop of the image is taken to train the model. This technique helps the model become more robust to changes in the position and orientation of the object in the picture.
[69]	*Translation*	Translation in data augmentation involves moving an image or object horizontally or vertically by a certain number of pixels. This creates new versions of the original image that can be used to train ML models.
[70]	*Color Jittering*	Color jittering is a data augmentation technique very useful in computer vision and image processing. It involves applying small random perturbations to the color channels of an image to create new training examples. Color jittering is used to increase the variability of the training dataset, which can enhance the performance of deep neural network models by making them more potent to variations in lighting and color.
[71]	*Noise Injection*	Noise injection is a common technique used in data augmentation, which involves adding random variations or distortions made to training dataset to increase the robustness of a machine-learning model.
[72]	*Adding Occlusions*	Occlusions refer to covering part of an image with an opaque object or layer, simulating real-world scenarios where objects can obstruct parts of an image. By adding occlusions to the images, we can make the model more resistant to variations in the data and improve its generalization performance.
[73]	*Elastic Transformation*	In an elastic transformation, a grid of tiny cells is initially created from the image. The original image is then smoothly deformed as each cell is subsequently randomly moved. A number of factors, including the size of the displacement and the smoothness of the

	deformation, affect how much displacement occurs.

Among the above mentioned data augmentation techniques, the most commonly applied technique is image flipping [67], which is applied for increasing the training set from the pre-existing set. The data augmentation reduces the chances of overfitting.

Table 5. Various Datasets Used

Dataset	Crops present in Dataset	Description
[74]	*Apple, Blueberry, Cherry, Corn, Grapes, Oranges, Peach, Pepper, Potato, Tomato, Soyabean, Strawberry, Raspberry, Squash*	• A total of more than 54306 images of leaves over a consistent background. • 38 groups are used to classify plant-disease pairs across 14 crop species. • A single digital camera was utilized to take exterior photographs of the leaves on sunny or cloudy days after they had been removed from the plant and placed on a gray or black backdrop.
[75]	*Maize*	• 18222 pictures of maize plants with 105,705 NLB lesions are included in the dataset. • Lesions of northern leaf blight (NLB) were annotated in each image.
[76]	*Paddy*	• The Paddy Doctor dataset comprises 16,225 paddy leaf pictures that were properly categorized into 13 classes.
[77]	*Rice*	• This collection comprises 120 images of diseased rice leaves. • The photos are split into three categories, with each class including 40 photographs.
[78]	*Apple*	• The collection comprises 3651 RGB pictures of different apple foliar disease signs. • The images contain images of apple scrap, cedar apple rust, complex disease symptoms, and healthy leaves of apples.

Among the above-mentioned datasets, PlantVillage has emerged as the most frequently employed dataset that has been used for training and developing deep learning-based plant illness detection and severity evaluation methodologies [79]. The dataset is divided into training and testing sets for the validation of the model [80].

3.5. Architectures

CNNs are a specific kind of neural network system which are typically employed for tasks consisting of image and video recognition. Pooling layers, layers of convolution, and fully linked layers are among the layers that make up CNN's architecture.

Convolutional Layer: The layer of convolutional is the primary building block of a CNN as it applies filters to the input image to create feature maps. Each filter detects certain patterns in the input images, like textures, lines, as well as edges.

Pooling Layer: The size of the map of features generated via the convolutional layer shrinks with the help of the layer of pooling. To accomplish this, feature maps are put through a pooling function, such as max pooling. The feature maps' pooling function takes the maximal value from each local region.

Fully Connected Layer: The CNN's final layer is the fully connected layer. It uses the output from the layer preceding it to categorize the input visual. Each neuron in the fully connected layer is linked to every other neuron in the preceding layer, analogous to a typical neural network.

CNNs may also employ other separate sorts of layers, such as normalization layers, activation layers, and dropout layers, in addition to these. Depending on the particular task and the complexity of the input data, a CNN's architecture can change.

Table 6. Description of various architectures of CNN models

Reference	Name of Models	No. of Layers	Parameters (millions)	Size of Input layer
[81]	*AlexNet*	8	62.3	(256, 256, 3)
[82]	*VGG16*	16	138	(224, 224, 3)
[82]	*VGG19*	19	138	(224, 224, 3)
[83]	*GoogleNet*	22	4	(224, 224, 3)
[84]	*MobileNet*	53	13	(224, 224, 3)
[85]	*Pre-trained MobileNet-V2*	53	3.4	(224, 224, 3)
[86]	*MobileNet-V3*	28	2.9	(224, 224, 3)
[87]	*Efficient Net-V2*	10	24	Max (480, 480, 3)
[88]	*ResNet*	50	60	(224, 224, 3)

There are various training parameters used to train the model like learning rate, number of epochs, batch size, optimization algorithms, loss function, etc.

AlexNet

Designed by Alex et. al. [81]. In 2012, The ImageNet Large Scale Visual Recognition Challenge (ILSVRC)in 2012 was won by the (CNN) architecture AlexNet, which is widely regarded as a turning point in the development of deep-learning algorithms.

The AlexNet has an eight-layer architecture with 3 entirely connected layers and 5 layers that are convolutional. The initial layer of convolution incorporates 96 filters. The subsequent convolutional layer has 256 filters. The 3rd convolutional layer has 384 filters; the 4th convolutional layer has 384 filters; and the fifth convolutional layer has 256 filters. The output of the final convolutional layer is subsequently transmitted to the 4096-neuron fully connected layers, followed by an output layer of 1000 neurons, which is the same as the number of classes in the ImageNet dataset.

AlexNet also incorporates several key innovations that help the efficacy of models based on deep learning need to be enhanced.These include the use of dropout regularisation, which substantially decreases overfitting, and ReLU functions for activation, paving the way for more rapid training cycles. Additionally, AlexNet introduced the concept of data augmentation, which involves randomly transforming training images to increase the total number of records in the training set and improve performance of models for fresh data.

ResNet

The ResNet is a multi- layers of CNN block, with each block containing several convolutional layers, batch normalization, and activation functions usually ReLU [88]. The residual connections are added between each block, allowing information to be passed from one block to the next.

Utilizing residual connections is the main principle of ResNet., which allows information to be passed directly from one layer to another without being processed by intermediate layers. In other words, a residual connection provides a shortcut that facilitates the network to learn the identity functions for a particular layer more easily, which can be useful for avoiding the problem of gradient disappearance that can occur due to increased number of layers in a deep neural network.

On numerous computer vision tasks, such as image classification, object detection, and segmentation, ResNet produced state-of-the-art results. Its success has inspired many follow-up architectures, such as DenseNet and Wide ResNet, that also use shortcut connections to enable deep architectures.

VGG

The VGG architecture consists of a series of convolutional layers, followed by max-pooling layers, and then fully connected layers at the end. The convolutional layers use small filters (3x3) with a stride of 1 and the same padding to maintain the spatial dimensions of the input image. The spatial dimensions are reduced in half by the max-pooling layers that employ a 2x2 filter with a stride size 2.

There are several versions of the VGG architecture with varying numbers of layers. The most commonly used versions are VGG16 and VGG19. VGG16 consists of 16 layers, including 13 convolutional layers, 5 max-pooling layers, and 3 fully connected layers. VGG19 is similar to VGG16 but with 19 layers [82].

The fully connected layers at the end of the network are used to perform the final classification. The output of the last fully connected layer is fed into a softmax function to obtain a probability distribution over the possible classes.

The VGG architecture has been widely used as a baseline model for many computer-vision tasks, such as object detection, segmentation, and transfer learning. Its numerous parameters, however, make it computationally and memory complicated to train and deploy.

3.6. Training Parameters

Training parameters are the configurations that are explicitly provided by the trainer to train the machine learning model. These parameters decide how the model will be trained and how the data will educate the model that will be provided to them. There are various training parameters used to train the model like learning rate, number of epochs, batch size, optimization algorithms, loss function, etc.

Table 7. Training Parameters

Reference	Techniques	Description
[89]	*Learning-rate*	The periodicity through which a model alters a parameter at the time of training.
[90]	*Epoch Size*	Epoch size is defined as, how often the complete data set is running through an algorithm in one epoch.
[91]	*Batch size*	The size of the training dataset which is present in a single-batch. The batch size selections impact a model's testing accuracy.
[92]	*Optimization algorithm*	These are the algorithms which are employed to enhance the model's performance and accuracy by tweaking the model's hyper-parameters.
[93]	*Loss function*	These techniques are employed to assess an algorithm's efficiency in

		modeling a dataset. For better outcomes, the loss function's value should be low.

The combination of the training parameters should be done optimally as they have a remarkable effect on the model's performance. The nature of different parameters affects the accuracy differently. A small value of learning rate will halt the process, but a high learning rate might cause the model to converge prematurely leading to an unacceptable outcome [89]. Also, a larger batch size produces better performance than the one with a lower batch size [46].

3.7. Evaluation Metrics of the Network Learning Performance

Evaluation matrices are used to evaluate the effectiveness of the training model. These matrices give us an idea of how better our model will perform for the given data. Depending upon the values of the evaluation matrices we can change the value of hyperparameters to increase the model's reliability. There are various evaluation matrices used to evaluate the performances of the model and a few of them which are mostly used are: a). Accuracy b). Precision c). Recall d). F1-Score e). AUC-ROC Curve.

Table 8. Evaluation Metrics

Reference	Techniques	Description
[16]	Accuracy	Accuracy tells us how near it is to the actual value. The proportion of correct estimates to all predictions serves as the basis for this calculation.
[16]	Precision	It is defined as the accurate classification of positive samples to all positive samples that have been classified. Another way to describe precision is how effectively a model will be able to recognise the proper samples. If the dataset is unbalanced, precision is insufficient to determine the classification's performance.
[34]	Recall	It is the proportion of values that were successfully predicted to all other values present in a given class. It also goes by the name "sensitivity." This computation is based on the proportion of accurate positive predictions to all positive cases.
[34]	F1-Score	F1-Score type that can be used to measure recall and precision. It is the harmonic mean of precision and recall when the same weights are given to them. The F1 score can be utilized for binary classification issues in machine learning. The F1-score varies between 0 to 1, where 1 corresponds to the highest precision and recall while 0 to the worst. The F1 score is also helpful when the dataset is disproportionate.
[94]	AUC–ROC curve	It is an evaluation metric employed when the distribution of datasets is uneven and the amount of samples in each class are not uniform. The true positive rate and false positive rate are two metrics that are shown on an AUC-ROC curve. The model performs better at predicting the correct class if the AUC-ROC value is high.

Among the above-mentioned table, the AUC-ROC curve is among the most renowned matrices applied for evaluation and discrimination purposes [95]. The AUC-ROC curve is used when the distribution of the dataset is uneven and each class has no uniform number of samples [94]. The F1-score and the accuracy are the evaluation metrics which are also used for evaluation purposes. The greater the value of the accuracy suggests a greater performance of the model.

4. Conclusion

The range of challenges and peculiarities of real-world situations make it more challenging to semantically catalogue the data in representative data sets with a sufficient number of labeled samples. In order to develop more useful machine learning approaches, it becomes vital to solve this problem. On the basis of above findings which demonstrate the significant advancements in CNN's plant disease prediction techniques. It was possible to demonstrate that traditional architectures combined with optimization and customization methods present significant accuracy despite the dataset's complexity, which is made up of images collected in actual agricultural environments. Numerous approaches are increasingly likely to offer novel CNN designs based on the process of recognizing plant illnesses. However, it was discovered that as these structures grew more specialized, it was detrimental to the type of crop being studied.

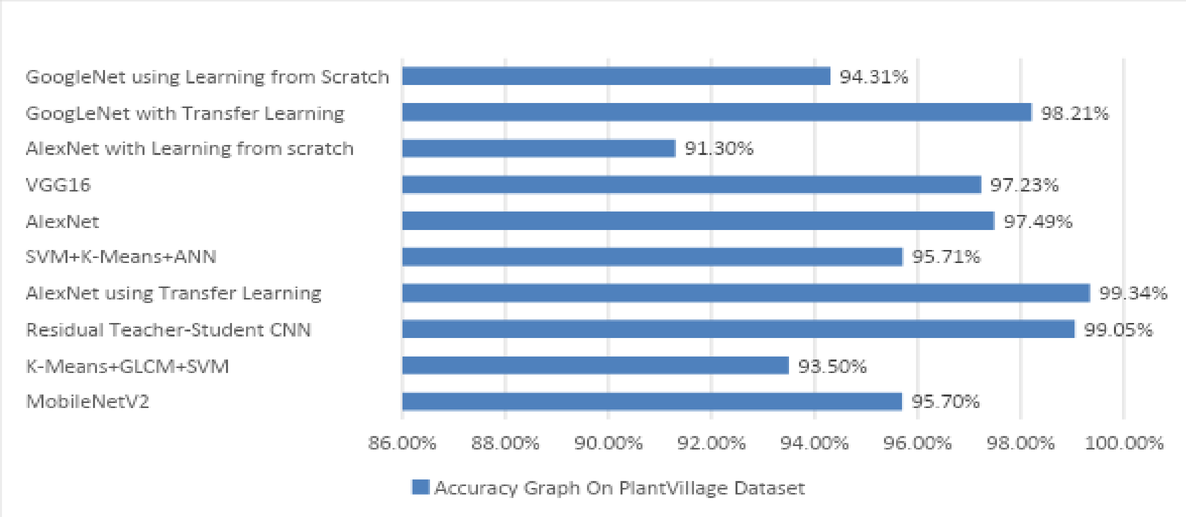

Figure 3. Accuracy Graph on PlantVillage Dataset

K-means clustering, CNN, VGG, AlexNet, GoogleNet, Compact CNN, DenseNet and Fast R-CNN are the principal architectures for detecting plant diseases. These architectures can be used to evaluate both leaves in sound health as well as leaves in infection. Only a few of the issues with these techniques include the effect of additional metadata on the final image, technique refining permitting a particular vegetation leaf ailment, and technique mechanization to maintain routine observation of illnesses of plant leaves in actual field situations. The analysis found that while this approach to disease detection has significant drawbacks, it shows great promise for detecting ailments in plant leaves. On the basis of the above reviewed paper existing research has potential for improvement.

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