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A Comprehensive Review of Plant Disease Detection Using Deep Learning

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ABSTRACT

The research on maize diseases is described in this study of current literature. The most valuable findings are extracted from researchers' previous work and presented in a compiled form. The article discusses the problem of detecting plant diseases using deep learning techniques. Plant diseases can cause significant damage to crops, and early detection is essential for effective treatment. The study demonstrates how the model and approach may be designed from a new viewpoint, which can then lead to improved outcomes. Following this, datasets that are accessible to the public are described and identified, and then the proposed procedures and the findings are tested and verified using these datasets. Performance metrics along with their respective formulae are discussed to demonstrate how these measures might be used to evaluate the effectiveness of research activity.

Keywords: *Deep Learning; Computer Vision; Machine learning; Corn; Plant Diseases*

1. INTRODUCTION

It is known that agriculture is the backbone of many countries and it depends on different methods for farming goods and products keeping in view their quality and quantity. Thus, it compelled many researchers to implement image-processing methodologies for the detection of plant diseases [1]. Amongst plant diseases, corn plants are significantly affected by several factors. One of the emerging areas in image processing is artificial neural networks where the results are accurate and easy to analyze [2]. GUI-based detection systems [3], throughput and subject-based detection systems [4], and intuitionist fuzzy-based systems [5] are some other techniques. Corn plants may have any specific diseases from a given range of diseases depending on the cause. Computer vision techniques are applicable and helpful in the recognition of various diseases [6]. Different plant diseases and detection methodologies are proposed in the literature [7]. Other innovative approaches like imaging are used to detect and automate the disease detection process. These kinds of modern and innovative methods work faster without any personnel monitoring. Zheng et. al reported 87.99% accuracy and 86.87% accuracy using imaging techniques [8].

Plant diseases are mainly caused by living organisms. Thus, biotic factors are considered by most researchers. On the other hand, abiotic factors are non-living factors like hail, chemicals, storms, etc. Both factors affect and decrease crop yields [9]. The focus is on the detection of plant diseases that are caused by biotic factors. Different techniques are used for identifying plant diseases through pattern classification [10]. Various works are done on bacterial diseases and fungal diseases. Abiotic factors result in spots, cankers, mildew, etc. Biotic and abiotic have different effects on plants and their leaves. Treating biotic factors have a greater possibility rather than abiotic factors because they are treated with medicines and pesticides. They help plants to avoid diseases. These diseases are divided in three categories: viral, bacterial and fungal diseases. The categories of Plant diseases are shown in Figure 1.

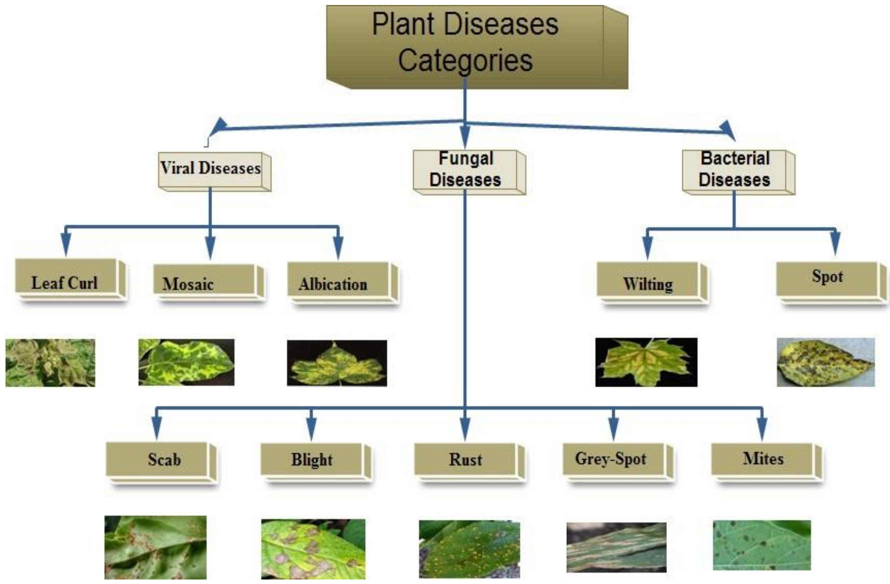

Figure 1. The Categories of Plant Diseases

This article considers only innovative imaging methodologies and techniques for detecting diseases in a plant. Researchers have utilized different methods of machine learning for the accurate examination of diseases in corn plants. They observed that diseases in corn plants and many other plants can be first detected through their leaves because leaves are the prominent part that shows signs of getting affected due to disease or any other circumstances. The major contributions of the article are as follows:

- It discusses the importance of using a standardized dataset for evaluating the performance of plant disease detection systems.
- It emphasizes the need for better feature extraction techniques to improve the accuracy of disease detection.
- It highlights the difficulty of detecting diseases at early stages, and it suggest that future research should focus on addressing this challenge.

2. RELATED WORK

This section of the article presents information about related work that has been conducted in the field of corn disease detection and classification. It also covers a review of the existing literature, publicly accessible and available datasets, and performance metrics for classification performance. The main architecture for the detection of disease in the plant is based on several modules: acquisition of the image, pre-processing of obtained images, segmentation, extracting features, and feature fusion. This architecture is classified into two modules: training and testing. For achieving this purpose, deep learning models are used for the identification of diseases in corn plants with the help of training and testing [11]. In the training phase, the image is captured from a specific part like a leaf of corn, and also gathered from different datasets. Then this image is passed through the image processing step to correct geometric representation, noise reduction, remove blurriness, and grey level correction. For this purpose, automatic techniques are beneficial. Various advanced technologies are helpful in the detection of plant diseases. In the current situation, no real-time sensors are available for detecting diseases in plants. So, advanced techniques will be helpful and should not be expensive and labor-intensive. After preprocessing, segmentation techniques are applied to separate the area of interest from the remaining background and identify the regions from training infected leaf images. In the last step, those features are extracted and put in a classifier for training. In testing, test images are taken and then passed through pre-processing, segmentation, and extraction of feature modules. The trained and prepared classifier will then be able to recognize the test image as a healthy or diseased leaf of corn. The performance rate of the plant detection system is assessed through a popular measurement known as accuracy. Other performance measures like recall rate, success, and precision rate are also used for assessing the applicability of such detection systems in the field of plants, their diseases, and classification. Different images based processing techniques are available to check these performance measures [12]. Different steps to detect and categorize diseases in plants are shown in Figure 2 below, and these steps are discussed in the next sections.

The flow of the article is as follows: section 3-8 discusses different techniques of image acquisition, pre-processing, segmentation, feature extraction and selection and classification proposed and used by different researcher. The review of existing work on plant disease detection using deep learning with its challenges and limitations are also discussed in these sections. Next, it discusses the publicly available dataset of plant leaf images and the performance measures used in the existing methods are discussed in section 10. Section 9 describe the research findings of this survey paper and the last section is to conclude the survey by discussing the implications of findings and by suggesting future directions for research.

3. IMAGE ACQUISITION

Image acquisition is the first and most important step as accuracy is greatly dependent on the samples of an image taken for the training purpose. So, image acquisition is a step where images of corn are acquired and captured from different sources [13]. In the domain of detecting diseases using leaf images, researchers use some popular and well-known datasets [14]. The University of Minnesota Extension provides various image sets with theoretical detail and explanation. Some research centers give privileges to access the datasets for work . Some used the datasets for image acquisition from single culture instead of taking full-fledged datasets [15] while others used a cross-cultural dataset of plants for image acquisition [16]. A lot of studies have been done on image datasets of corn collected under controlled conditions of environment or with complex backgrounds [17] while some chose scanned images [18]. The quality of an image is also dependent on the camera used to collect data and on its orientation. Researchers mostly used a digital camera for capturing leaf images with a perpendicular axis toward the leaf plane. Software tools with CCD cameras are also in use for capturing the image [19]. CCD cameras with XG-711 are also available for this purpose [20]. Android phones are used for taking images from fixed distances [21]. Some researchers also used the multi-spectral camera to take high-quality images of the crop [22]. A hyperspectral camera is utilized for the detection of infected leaves in tomato leaves [23]. Besides different techniques, some prefer to propagate the corn plants in a suitable environment and then take their images [24].

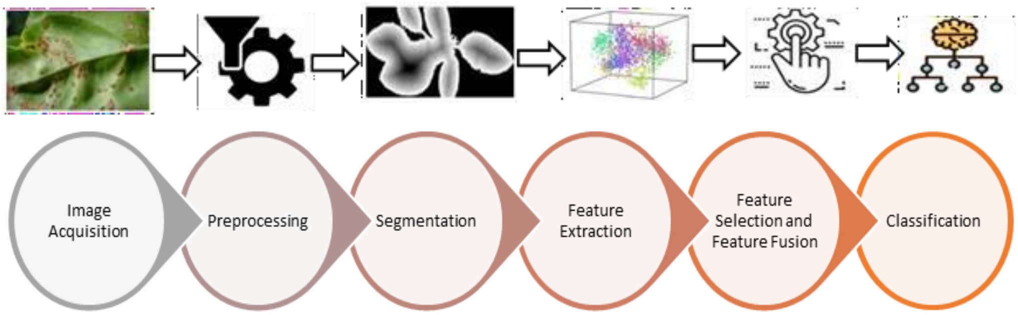

Figure 2: General Steps to Detect and categorize Plants diseases

4. PRE-PROCESSING

Pre-Processing is a phase where distortion is removed from the corn image to improve it. It is important for better processing of images. Many techniques exist for removing noise and distortion among which popular techniques are cropping, smoothing, color and space conversion, and enhancements. Techniques that are applied based on the quality of images include edges, color, and histogram matching [25]. Multiple techniques are also used for enhancing the images. For instance, [26] converts the images into HSV color space and then used histogram equalization on it. It is also preferable to use image pre-processing techniques with artificial intelligence for improved results [27]. Computer vision algorithms are also helpful in the phase of pre-processing for the directional-based transformation of images [28]. HSV, which works on Hue, Saturation, and Value, is the most common technique used for pre-processing images [29]. Another common technique similar to HSV is HIS. Arivazhagan et. al proposed a technique that mainly focuses on preprocessing where the green pixels mask is prepared from an RGB image [30]. The only difference in HSI is that it used intensity rather than value. There exist many other approaches like YCbCr [31], RGB [32], spot texture, [33], color description using MPEG-7 standard descriptors [34], and CIE 1976 [35].

Automatic segmentation can be done by getting new color space from RGB conversion [36]. Once the color transformation is done after the removal of noise, required and more suitable filters are applied for getting desired enhancements. These filters are used for brightness and contrast in the image. For removing noise and other distortion, researchers prefer to use rank filters [37], texture field extraction [38], and median filters [39]. Laplacian filter [40] and thresholding [41] are other filters used for making the image sharp. Using filters is one way to enhance the image of corn. There are other methods also like histogram equalization, anisotropic diffusion, spatial low pass filter, neighborhood mean, and Gabor wavelets [42]. With image enhancement, cropping the corn image is also necessary when the image is captured or taken in an uncontrolled manner. The unnecessary part of the corn image is cut off and removed from the image to avoid unnecessary details and incorrect results. Cropping can be done in two ways; either manually or automatically by using various functions [43].

5. SEGMENTATION

In the digital processing of the image, segmentation means to do partitioning the image into various segments. These segments are based on a set of pixels. Segmentation helps to locate the object and its boundaries within a corn image. A corn image can have a single object or multiple objects. Also, features extracted from segmented corn images help us to easily identify the image of the healthy or infected parts of plants. Segmentation is achieved by using one or multiple techniques. For instance, the identification of infected or healthy parts with the help of extracted features is done with histogram peaks [44].

Other techniques based on segmentation include threshold, color-based segmentation, locality, edges, etc. These techniques work well and the results are efficient if such methodologies are applied in the identification of diseases in corn plants. Edge-based techniques used Canny edge detection [45] and Sobel edge detection of objects [46]. Some other studies explored Grab cut segmentation and Genetic algorithm in this type of technique [47]. Segmentation techniques based on threshold are constituted of Otsu segmentation methods [48] and the entropy concept [49]. HSI space used manual settings of the values of the threshold to get an effective segmentation [50]. Seeded region growing (SRG) performs automatic segmentation of images to get efficient results [51]. Color-based segmentation helps in identifying infected regions by segmenting the infected part from the healthy part with the help of color variation. As color varies when the infected part is compared with the healthy part of corn, so it is easy to identify the diseased part with the help of color differentiation in the specific region of plant.

Studies show that K-means clustering is better in performance than Canny-based and Sobel segmentation. On the other hand, K-medoid segmentation is more relative to performing on images having noise. Grey level values and color intensities are used by Fermi energy-based segmentation and have shown better results than K means clustering and Otsu-based segmentation. Diseased and infected leaf areas can be directly extracted by using k-means clustering and saliency region threshold techniques [52].

This combination gives better results than multiple segmentation techniques including unsupervised clustering, k-means clustering; mean shift, and optimal and fuzzy techniques. The study explains and suggests that k-means clustering performance over C-means and fuzzy logic has more accuracy for the detection of disease in plants [53]. In short, the value adjustment especially threshold values are important in segmentation. The incorrect and less accurate threshold values lead to wrong results and cause to formation of erroneous images [54]. Such images of corn are sometimes difficult to restore in their original form. A summary of summary of existing plant diseases segmentation methodologies is given in Table 1.

Table 1. Summary of Existing Plant Diseases Segmentation Methodologies

Ref	year	Techniques for Segmentation	Description Methodology	Modality/Dataset
[44]	2012	Histogram Peaks	Identification of infected or healthy parts with the help of extracted features	Corn Images
[45]	2013	Edge Detection (Canny)	Edge-based technique for segmentation	Objects in Corn Images
[46]	2014	Edge Detection (Sobel)	Edge-based technique for segmentation	Objects in Corn Images
[47]	2015	Grab Cut Segmentation and Genetic Algorithm	Combination of techniques for segmentation	Corn Images
[48]	2013	Otsu Segmentation	Segmentation based on threshold	Corn Images
[49]	2008	Entropy Concept	Segmentation based on threshold	Corn Images
[50]	2010	HSI Space	Segmentation based on threshold	Corn Images
[51]	2011	Seeded Region Growing (SRG)	Automatic segmentation of images	Corn Images
[52]	2015	Combination of k-means clustering and saliency region threshold techniques	Combination of techniques for segmentation	Corn Images
[53]	2013	Comparison of k-means clustering, C-means, and fuzzy logic	Comparison of clustering techniques for segmentation	Corn Images
[54]	2009	Importance of value adjustment in segmentation	Importance of threshold value adjustment for accurate results	Corn Images

6. FEATURES EXTRACTION

Normally the image is interpreted by its color, shape, size, texture, and object features. Most commonly, the histograms represent the color intensity in the image. The texture is represented in the form of entropy, homogeneity, contrast, variance, etc. In the same way, the shape and size, concavity, convexity, roundness, borders thickness, eccentricity, the area covered, etc. are assessed. There are two types of datasets; heterogeneous and homogeneous datasets. Homogeneous works well with the same type of dataset. But heterogeneous dataset works well on the combination of various features. Different features like color, contrast, texture, and shape are combined in different orders for heterogeneous datasets. But in the case of corn plant disease detection, texture works best for detecting infected parts [55]. For extracting the required features of images based on texture, studies use spatial variants of GLCM. This technique calculates the moment of inertia, entropy, energy levels, etc. of the unhealthy region of the plant. A spatial gray level dependence matrix (SGDM) of the infected image is also used to extract parameters and features from the images. The hybrid feature technique is also used for extracting the features. It uses the combination of two or more texture-based functions including structure, discrete cosine transformation DCT, difference operators, and decomposition of wavelet packets for efficient disease detection.

Recent studies show that different properties of affected corn leaves are used with the combination of two or more other properties. For example, some combined color with texture features and some combined shape features with color to detect which type of disease is affecting the plant [56]. Researchers are using such kinds of hybrid systems and techniques because they provide better results rather than applying a single technique in a specified region of corn's leaf. Some hybrid approaches work only with color and shape while eliminating texture-based features. For analyzing shape features, mathematical formulas of the median, mean, SD, Quartile 1 and 2, quartile 3, and rule of average brightness are used. Recently, Eigen-based vectors and skew dive vectors are used for extracting features to detect diseases in cotton leaves [57]. Another research shows the use of local descriptors with the comparison of their performance on corn leaves. These local descriptors include SURF, HOG, SIFT, DSIFT, and PHOW. The results analyze that the performance of PHOW is better than other local descriptors [58].

7. FEATURE SELECTION AND FEATURE FUSION

Before developing a predictive model, the selection of features is an important step to reduce the input size of the corn dataset. Only enhanced and required images of corn will be selected for classification and detection. The best feature selection approaches are hybrids such as entropy, skewness-based covariance factor, and PCA score [59] [60]. Some researchers adopt the skew divergence method for feature selection to enhance their results. These selected features are provided to SVM. Different features based on color, Gabor, and GLCM are selected for the fusion of features [61]. The larger the input images of corn are, the more accurate the results will be.

8. CLASSIFICATION

Classification is one of the main steps in detecting the disease in the corn plant. The leaves of corn plants are classified based on identified images of diseases. Researchers introduce different improved versions of software that do accurate and fast classification [62]. These technologies and software use identified green pixels and then apply the Otsu threshold method. Classification is a step-by-step procedure to get the results. In the first phase, training is given to the classifier by giving different corn images from the trained dataset. After training, testing is done by giving test images to the trained classifier and check that whether the classifier recognized and identified the image with its correct labels.

After training and testing, the classifier should be able to identify the diseased and healthy images of the leaf [63]. Recent studies explore different classifiers relevant to machine learning techniques to detect the disease in corn. Aakif et. al proposed a shape-defining feature along with Fourier descriptors which gives an accuracy of 96 % on two datasets [64]. Recent research shows that discriminating against the disease based on texture is 83%. While the discrimination rate based on shape is 55% [65]. So, the texture as input for the detection of diseases is better due to having an accuracy rate more than shape. Supervised learning requires a dataset as input while unsupervised learning algorithms give responses without labeled data. A third class also exists which is between supervised and unsupervised learning, known as semi-supervised learning [66]. Researchers categorized semi-supervised under a special class of supervised learning methods. The semi-supervised learning used a mixture of labeled and unlabeled training datasets. There are a lot of classification techniques used popularly in the field of identification of diseases, especially in corn plants. Researchers explored these classification techniques and divided them into various groups along with sub-categories.

Among these techniques, few are giving good performance than others and do accurate identification of diseases. These are mainly based on fuzzy logic, K-means, SVM and sigmoid, etc. SVM methods which are based on the Radial basis function give the best performance of disease detection in plants [67]. In this section, classification and its techniques are explored. It will analyze and discuss different classifiers to identify diseases of plants found in different cultures. The purpose of the discussion is to identify the best classifier system. Sometimes, the researchers combined different techniques to get better and more efficient results e.g., using a neural classifier along with SVM [68]. It depends on the scenario where these techniques should be applied and in which manner. Classification also specifies and discusses how much damage is done to corn leaves. Then, it detects the types of disease. After identifying the disease, the advanced classifier also suggests how to treat the plant and in which way. The automated approach of a futuristic decision support system [69] focused on classifying the diseases in soybean. This decision support system will be fed with inputs provided by the farmers over mobile internet to classify leaves as healthy and diseased using SVM.
The detail given below in Table 2 shows the classifiers and their categories based on supervised learning, unsupervised learning, and other techniques. The explanation is provided in the subsections mentioned below:
Different researchers used different classifiers in their research study and development. Some of the proposed new classifiers while others compared the results of different classifiers.

Table 2. Summary of Existing Methodologies for Plant Disease Detection

Ref	Year	Methodology	Modality/Dataset	Accuracy
[70]	2023	pre-trained Efficient DenseNet model, reweighted cross-entropy loss function	PlantVillage dataset	97.2%
[71]	2023	K-means clustering, SVM, principal component analysis (PCA), and Gray-level co-occurrence matrix (GLCM)	PlantVillage dataset	98.97%
[72]	2023	support vector machine classifier and convolutional neural networks	Rice plant diseases, paddy crops	91.45%
[73]	2022	R-CNN, SSD, VGG16, Yolov4	Sugar beet leaf disease	96.47%
[74]	2022	MobileNetV2, AlexNet	PlantVillage benchmark dataset	96.54% and 97.87% for MobileNetV2 and AlexNet
[75]	2022	Generative adversarial network and deep convolutional neural network	Tomato plant leaf disease	99.74%
[76]	2023	Random forest (RF), support vector machines (SVM), naïve Bayes (NB), and deep learning convolutional neural network (CNN)	Tomato viral leaf diseases	95%
[77]	2021	Use of chemicals, crop rotation, and tillage	Fungal pathogens	75%
[78]	2021	Transformation, contrast stretching, scaling, rotation smoothening, spotted/lesions segmentation, and classification using classifier models.	COFI lab images	87.99%
[79]	2021	Classification using neural network, mean average precision method on the developed model.	corn Images	93%
[80]	2021	Single shot detector and proposed CNN model	Own dataset	96.88%
[81]	2021	Visual Geometry Group (VGG)-13	PlantVillage Dataset	95.12%
[82]	2021	Novel hybrid model based on Convolutional Autoencoder (CAE) network and Convolutional Neural Network (CNN)	PlantVillage Dataset	98.38%
[83]	2021	partial least squares (PLS) regression, VGG-19, PLS-based parallel fusion, and PLS projection method.	Tomato, Corn, and Potato Images from PlantVillage	90.1%
[84]	2021	Conversion into RGB format, R band feature extraction, optimized probabilistic neural network (OPNN) for classification.	Images caught from Farmland	95.5%

9. DATASETS DESCRIPTION

The dataset of corn-diseased leaf images is used in research work. This dataset contains four classes and the data is imbalanced in each class. The classes contain a different number of images. The Corn or Maize leaf disease dataset exists publicly and is available for everyone to download and use for their research work. The classes of dataset include the class of blight, leaf spot, rust, and healthy images [85]. An optimized dense CNN is applied to the dataset having common diseases [86]. Some researchers apply the CNN model for corn leaf diseases as a real-time recognition of disease [87]. Deep convolution neural networks are applied to the dataset taken from multiple sources like different Google websites and plant villages etc. These networks are the connection between existing optimized-based models and the latest neural network architecture where the novelty is brought for improved results. Besides training on the own or proposed dataset, it is preferable to perform transfer learning for the recognition of images of maize disease leaf [88]. Some sources contain a large amount of data which contains the dataset of many other plants but only desired one is selected and used for research purposes. Subdivisions can also be applied to the dataset to increase the images and their accuracy. The corn leaf dataset is also used for the nano-coating of edible biomass which is then used as a drug in the biomedical field [89]. The Plant Village dataset is a widely used dataset by researchers containing 54303 images of healthy leaves and unhealthy leaves divided into 38 classes. Kaggle is also a popular dataset collection site where 50,000 datasets are available publicly. The detail of the datasets is given in Table 3.

Table 3. Summary of Publicly Available Plant Diseases Datasets

Ref#	Corn/maize Datasets	Total images	Healthy Images	Diseased Images
[87]	Plant village dataset	3823-images	1162-images	2661-images
[90]	Multiple sources dataset	500-images	60-images	440-images
[91]	Kaggle (only maize plant dataset)	15408-images	4648-images	10760-images

10. RESEARCH FINDINGS

The main findings of the survey after all the above discussion are as follows:

- There is a lack of a standardized dataset for evaluating the performance of plant disease detection systems. Different studies used different datasets, making it difficult to compare results and to assess the generalizability of different methods.
- There is a need for better feature extraction techniques to improve the accuracy of disease detection. The current feature extraction techniques were not able to capture all of the relevant information in plant leaf images. Future research should focus on developing more sophisticated feature extraction techniques that could improve the accuracy of disease detection.

11. It is difficult to detect diseases at early stages. The most current methods were only able to detect diseases at later stages, when the damage to the plant was already severe. The future research should focus on developing methods that could detect diseases at early stages, when they could be treated more effectively.

10. PERFORMANCE EVALUATION MEASURES

The performance evaluation measures are used to identify the performance of disease detection in corn plants. The common method to analyze the results as an overview is through a confusion matrix, which is mainly based on four outcomes i.e., True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). ROC is also widely used to detect the ratio between Sensitivity and False Positive rates. Table 4 shows prominent performance metrics that are widely used in research and are given below.

Table 4. Performance Measures

Performance Measures	Evaluation
Accuracy	$\frac{T^P + T^N}{T^P + T^N + F^P + F^N}$
Precision	$\frac{T^P}{T^P + F^P}$
Sensitivity/Recall	$\frac{T^P}{T^P + F^N}$
Specificity	$\frac{T^N}{T^N + F^P}$
F1-score	$\frac{2 \times \mathrm{P} \times \mathrm{S}}{\mathrm{P} + \mathrm{S}}$

11. CONCLUSION

The survey on plant disease detection using deep learning provides a comprehensive overview of the latest research and advancements in this field. The survey covers various aspects of deep learning approaches for plant disease detection, including different techniques used for image processing, feature extraction, and classification. Based on the review of the literature, it can be concluded that deep learning techniques have shown promising results in the detection and classification of plant diseases. Convolutional Neural Networks (CNNs) are the most commonly used deep learning algorithm for plant disease detection due to their ability to learn complex features and patterns from images. However, there are still some challenges that need to be addressed to improve the accuracy and efficiency of plant disease detection systems. These challenges include the lack of a standardized dataset for evaluation, the need for better feature extraction techniques, and the difficulty in detecting diseases at an early stage. Overall, the survey highlights the potential of deep learning techniques in the field of plant disease detection and provides insights into future research directions in this area.

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