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Survey on Leaf Disease Prediction using Image Processing and Artificial Intelligence

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***Abstract*— Major productivity and financial losses, as well as decreases in both the quality and quantity of food products, are caused by plant disease (PD). PD identification is now receiving increased attention in the field of agricultural monitoring. Changing from one method of disease prevention to another is a major challenge for farmers. Traditional methods for identifying PD have relied on the naked eye inspection by professionals. In this work, we discuss how an automated approach for identifying PD would contribute to improvements in agriculture. Diseases can be managed more effectively with the use of early detection. Much research has been conducted to evaluate the potential of Artificial Intelligence (AI) approaches for precision agriculture. Despite the variety of applications, a few gaps in PD research must still be filled. Therefore, it is necessary to create a database of already-existing applications and to determine the obstacles and possibilities to move forward with the development of tools that meet farmers' demands. This survey provides a thorough analysis of the various studies conducted on the use of AI for PD identification. This paper walked over the fundamentals of PD analysis, including the structure of PD, freely accessible datasets, processing methods, segmentation techniques, feature extraction approaches, and categorization models. Finally, the difficulties of employing AI for PD detection are also presented. The primary goal of this literature review is to help new researchers learn more about automated PD categorization.**

Keywords— Plant Disease, Leaf, Artificial Intelligence, Pre-process, Agriculture, Segmentation, Accuracy, Feature Extraction

I. Introduction

The number of people living on Earth is rising quickly. A study published in [1] estimates that in 2030 the global population will have hit 8.5 billion. To meet the needs of an expanding population, there is, therefore, an immediate requirement to increase agricultural output. Environmental factors that favour the growth of microorganisms include temperature, humidity, and precipitation. An increase in environmental pathogens increases a plant's susceptibility to disease. This decline can mostly be attributed to the prevalence of crop pests and diseases. The ability to accurately predict the spread of disease is crucial for protecting plants from potential threats. Consequently, it contributes to increased crop yields and general productivity.

The economic costs of food security at the national and global levels are amplified when crop yields are reduced due to PD. 20% to 40% of worldwide food production losses are attributable to PD, as per the report of FAO in 2017. It is estimated that PD accounts for 13% of the global crop output loss [2]. These numbers demonstrate why checking plants for illnesses is essential for protecting crops. However, it is necessary to determine the underlying causes of PD.APD can only occur if the pathogen, host, and environment are all present. The aforementioned factors together create the triangle of PD in Fig. 1.

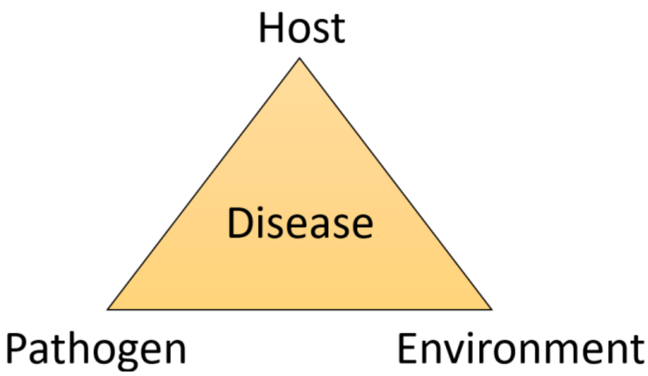

Fig. 1. PD Triangle.

Most PD spread from the roots up the plant. One infected plant can quickly become a breeding ground for disease. Monitoring crops closely is essential for stopping the spread of diseases [3]. Sometimes the first signs of a plant illness won't show up until after pollination has taken place. Various PD cause damage to specific body systems. Foliar diseases, which manifest themselves in plant leaves, are mostly diagnosed by plant pathologists through visual examination. Today's studies rely heavily on Computer Vision (CV), machine learning (ML), and deep learning (DL) to analyse leaf images and diagnose plant illnesses [4]. Essential features of a reliable PD diagnostic technique

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include early-season detection, recognition of numerous diseases in various crops, and simultaneous identification of several diseases. In addition to providing advice for stopping the spread of the disease, the report also offers estimates of the severity of the outbreak and the number of pesticide applications.

Accurate disease diagnosis is crucial for precision agriculture. The manual visual inspection required by older techniques of PD identification and monitoring is too costly, time-consuming, and expert-dependent to be practical for precision agriculture. The accuracy of such methods is also likely to be impacted by human bias and weariness [5]. To better these inefficient methods, researchers have explored the application of image processing algorithms on leaf images for disease detection.One of the first studies to employ standard image processing for PD established a computerised disease diagnosis system in 1983 using static and moving images as well as videos of tomato and fern plants[6]. Some evidence suggests that computer-based methods using image processing to quantify streak disease in maize are more accurate than optical inspection alone. Over the past 30 years, conventional image processing techniques have risen in popularity due to their capacity to provide objective disease diagnosis. However, because different research assigns varying degrees of importance to different traits, these methods need time-consuming and potentially biased human feature extraction.

Around 20 years ago, when its agricultural and PD uses were investigated and reviewed inan article [7], ML ignited interest in PD identification. As computational power, storage capacity, and data sets have increased, DL has become the method of choice for disease diagnosis. However, DLrequires massive datasets that may contain hundreds of images [8]. We reviewed 59 studies that built models for identifying and forecasting the severity of PD using a variety of imaging data collection systems. PD, Image Processing, and AI were used to find the studies in IEEE Xplore, Scopus, Science Direct, and Google Scholar.

II. Process Flow

The process of autonomous PD prediction using images contains five important divisions. First, the plant leaf image acquisition. The acquisition of images can be done in two ways, the researcher can collect data using a camera and the next is the usage of online data. Second, the pre-processing of images. The collected raw images are processed to remove the impurities from them. Pre-processing resizes, normalization, and augmentation are involved. Third, the affected area should segment from the healthy one. The segmentation process can be of various types such as threshold, edge-based, cluster-based and region-based. Fourth, feature extraction is applied to retrieve the important features. The feature extraction depends on various parameters like colour, texture and shape. Finally, after feature extraction, the classification is done to categorize the leaf as healthy or diseased. The complete research flow of PD detection is illustrated in Figure 2.

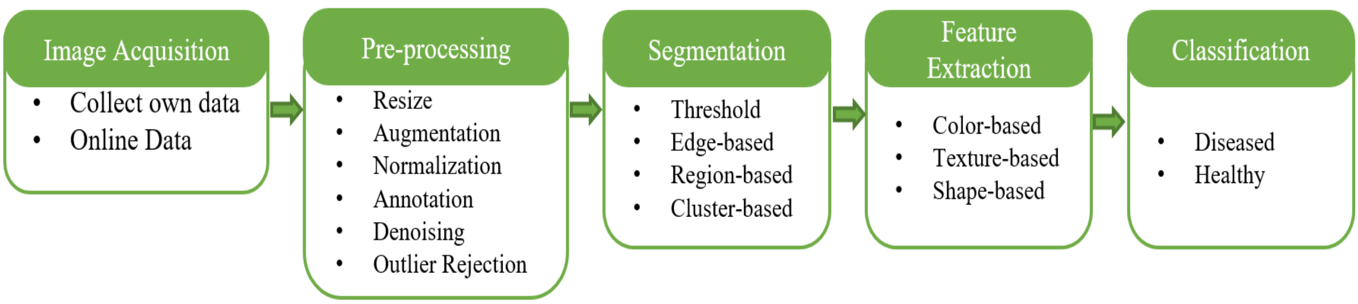

Fig. 2. Research flow of PD classification using AI

III. Data Acquisition

For researchers to create algorithms and computer scientists to train their models to recognise PD from images, appropriate datasets are necessary. The acquisition of image data is the first stage in identifying PD. Autonomous solutions necessitate large datasets containing hundreds or thousands of images. Table 1 lists some typical PD datasets that are available online. The PlantVillage dataset is the most commonly utilised. However, the majority of the researchers in the examined papers chose to acquire custom datasets that were not made public. The researchers can use the online data or they can collect their data from the fields.

TABLE I. Benchmark Dataset

Dataset	Crop	Acquisition Environment	Dataset size	Reference
PlantVillage	Multiple	Laboratory	54304	[9]
Cassava Dataset	Cassava	Field	24,395	[10]
PlantDoc	Multiple	Field	2,598	[11]

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Insect Pest Recognition Database	Multiple	Field	75000	[12]
Image Database for Plant Disease Symptoms (PDDB)	Multiple	Field	2,326	[13]
APDA	Rose	Field	40	[14]
Tomato Pest Images	Tomato	Network	4263	[15]
Corn Disease Dataset	Corn	Laboratory	4188	[16]
Plant Disease Dataset	Multiple	Laboratory	125,000	[17]
Hops Disease Database	Hop	Field	1102	[18]
Maize Disease Dataset	Maize	Field	18,222	[19]
BRACOL	Coffee	Field	4407	[20]
DiaMOSPlant	Pear	Field	3305	[21]
Plant Pathology	Apple	Field	3651	[22]
Cotton Disease Database	Cotton	Field	2310	[23]

IV. IMAGEPROCESSING

Images of leaves can contain noise, low illumination, undesired background, and other issues. The results of applying categorisation algorithms to these raw collected images are inaccurate [24]. As a result, raw datasets must be pre-processed before being provided as input to the model. This is critical for reducing training time and increasing classification accuracy.Pre-processing like converting colour images to grayscale, resizing images, normalising, augmenting, cropping, outlier rejection and so on.

A. Resize:

The sizes of images gathered from various sources differ. The size discrepancy lengthens the training period of the model. As a result, before employing an AI model, the captured and/or acquired images must be resized. Image size uniformity can be obtained by cropping large images and padding zeros in small images. Images are scaled down or up based on the input layer of the AI model.

B. Augmentation:

AI model performance is very sensitive to the quantity of training data. If only a limited dataset is at hand, then additional information will have to be gleaned from elsewhere. Data augmentation methods include adjustments to things like luminosity, PCA jittering, vertical and horizontal shift, zooming, cropping, shearing, flipping, and rotating training images. Advanced methods, including Neural Style Transfer (NST) and Generative Adversarial Networks (GANs), are applied to AI in addition to the aforementioned conventional methods. These methods intentionally generate changed versions of images to increase a training data set [25]. Overfitting is avoided and model performance is improved as a result [26].

C. Annotation:

Annotation is a method for labelling images used in model training. Annotation for disease detection in plant leaves is performed by professionals with in-depth knowledge of the respective illnesses. Annotation methods range from bounding box annotations to pixel-by-pixel annotations of images. Annotation techniques such as the bounding box are often employed. In this method, a square or cube is tightly packed around the objective. The method has the problem of increasing the overall amount of background noise within the contained area. The problem of obstructed items arises for this method as well. Annotating images pixel by pixel requires object selection to be done manually. Annotating images pixel by pixel requires more time than using bounding boxes since it requires selecting objects along their boundaries individually. This method is laborious, time-consuming, and error-prone.

D. Normalization:

During normalisation, pixel intensity or dimension values are scaled to fit within a predetermined range. Pixel values in an 8-bit RGB image, for example, are integers between 0 and 255. Multiplying big input values with small weights disrupts a convolutional neural network (CNN) learning process. Therefore, it is necessary to standardise pixel values. All pixel values are divided by 255, the maximum value, to accomplish this. It provides all channel values between 0 and 1 without altering the appearance of images [27]. Light and dark areas of an image might distort it, but normalisation can fix that. It balances the weight of each feature and boosts the model's quality, speed, and accuracy of learning. Normalisation can be accomplished in many ways, like scaling, Z-score and Min-Max normalisation. Using the formula (1), Min–Max normalisation converts the data to a scale between 0 and 1.

$$new_x = \frac{x - min}{max - min}(new_{max} - new_{min}) + new_{min} \qquad [1]$$

Here, $x \rightarrow$ attributevalue, $max \rightarrow$ highest possible value of the provided attribute, and $min \rightarrow$ lowest possible value. The $new_{min}$and new_{max} have values of 0 and 1, respectively. Using this method, steady gradients can be achieved. Outliers, however, are not dealt with properly.

When performing a Z-score normalisation or standardisation, pixel values must be rescaled. Each pixel's value is calculated by subtracting the mean and dividing by

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the standard deviation of each dimension, as given in formula (2), zero centring is performed on the data.

$$z = \frac{x-\mu}{\sigma} \quad [2]$$

Here, $z \rightarrow$ standardized value, $x \rightarrow$ Attribute value, $\mu \rightarrow$ mean, $\sigma \rightarrow$standard deviation.

E. Denoising:

Denoising is the process of cleaning up an image without compromising its original details. Using this method with a noisy image categorization environment improves performance. Denoising methods used by scientists include the Mean, Gaussian, Median, Wiener, Small-window median, Bilateral smoothing, and so on. To blur an image and get rid of noise and details that are related to the noise, a common denoising procedure is a Gaussian filter. Median filters do not operate linearly. It gets rid of the noise that can't be added together. The Median filter works by applying a filter of 7x7, 5x5, or 3x3 pixels to an image's pixel matrix. The centre window pixel is replaced with the median of all pixel values. It does a good job of keeping edges sharp. In image processing, it helps get rid of the "salt and pepper" noise. Salt-and-pepper noise causes an image to have darker pixels in the lighter areas and vice versa. With Gaussian noise, the best filtering effect is achieved with the Mean filter or the Wiener filter.

F. Outlier Rejection:

An invalid or superfluous part from the images is ignored during outlier rejection. Example rejection criteria include poor resolution, irrelevance, blur; low intensity, noise, and duplicate images. The authors of [28] created a CNN model called organNet to filter out faulty or irrelevant images from a dataset.

From what has been said above, it is clear that pre-processing procedures are crucial in converting raw datasets into the appropriate form. To get classification outcomes more rapidly and correctly, the modified dataset is fed into an AI model. Pre-processing methods have varying mechanisms of operation and can be used on a wide variety of datasets. There are benefits and cons to every approach.

V. IMAGE SEGMENTATION

Segmentation is the process of separating an image into sections that have a strong link with the features of interest. Characteristics of a well-segmented image, such as the number of histogram peaks, make it simple to distinguish between healthy and diseased samples [29]. It has been demonstrated that segmentation methods based on edges, locality, thresholds, or colour are effective in detecting PD.

A. Threshold

Threshold segmentation is both the simple and one of the most extensively used parallel segmentation procedures in image processing. It is a typical segmentation method that divides the greyscale information of the images directly based on the grey value of several targets. The local and global techniques for threshold segmentation are distinct. In the global threshold approach [30], the target and background regions of an image are separated using a single threshold. The local threshold technique necessitates the selection of various segmentation thresholds to segment an image into numerous target regions and backgrounds.

The greatest interclass variance method (Otsu) is the most commonly used threshold segmentation approach because it selects an optimal threshold by maximising the variance between classes. Entropy-based threshold segmentation, minimum error, moment preservation, probability relaxation, simple statistical, co-occurrence matrix, and threshold methods are just a few of the techniques that can be utilised in conjunction with thresholds. The threshold method's strengths are in the simplicity of its calculations and the speed with which it operates. When there is a high contrast between the background and the target, for example, the segmentation effect could be attained. Correct solutions for image segmentation problems may be difficult to obtain when there is little to no grey scale difference or a considerable deal of overlap between the grey scale values in an image. Because of its sensitivity to noise and grayscale unevenness, induced by its focus on the grey information rather than the spatial information of the image, it is frequently employed in conjunction with other methodologies [31].

B. Edge-based

The item's edge appears as a break in the image's local features, such as a change in the grey value of the mutation, a shift in the colour mutation, a shift in the texture mutation, and so on [32]. The use of discontinuities to identify and separate image borders. In some cases, the grey value is not continuous, and there is always a grey edge in the image between surrounding regions with different grey values. Differential operators [33] are employed in the derivative calculation, which can be utilised to discover this discontinuity. It is a usual technique when segmenting an image to employ a spatial domain differential operator for parallel edge detection by convolving the image's template with the image itself. The most frequent first-order differential operators are the Roberts, Sobel and Prewittoperators. The second-order differential operator supports nonlinear items such as the Kirsch, Laplacian, and Wallis operators.

C. Region-based

One type of region segmentation algorithm is the regional growth method [34], which uses a sequential approach. Its core idea is to arrange pixels with identical properties into a region. The process begins with the selection of a "seed pixel," after which the similar pixels in the surrounding area are merged into the area around the seed pixel.

Advantages of regional growth include better boundary information and segmentation outcomes, as well as the separation of formerly related regions that share similar traits. The concept of regional development is straightforward and may be carried out with a minimum number of starting locations. The parameters for growth during cultivation can be determined at will. Last but not least, it can simultaneously select from several criteria. The high computational cost is a major drawback. Void and over-division can also result from noise and grayscale unevenness. Finally, the image quality is usually subpar due to the presence of shadows [35].

D. Cluster-based

There is no guiding principle behind the segmentation of images. However, because of the development of numerous new ideas and techniques in a wide range of disciplines, many distinct approaches to image segmentation have been combined. A "class" is a collection of entities that share some common characteristics. The clustering method adheres to categorization norms and regulations [36]. Using the feature space clustering approach, the image space pixels are separated into their respective feature space points. The feature space is segmented based on the aggregation of the features in the feature space, and the result is produced by mapping the feature to the original image space.

VI. FEATURE EXTRACTION

In the field of CV and image processing, features play a crucial role in the detection of important details. Features can be broken down into two categories: general features (GF) and domain-specific features (DSF). Application-independent features (GF) include things like colour, form, and texture [37], while DSF includes things like concepts and human faces that depend on the application. GF can be used for plants. Texture, colour, and shape make up the three main categories.

A. Colour-based

Colour features are widely employed for the extraction of visual features in the retrieval of information that is in the form of a video or image. The colour spaces or models are used to define colour, one of the most important features of images [38]. The translation or viewing angle does not affect the colour features. As the colour space is determined for an image, the appropriate colour features can be easily extracted from the image [39]. Colour space is utilised to specify the various colour features. Numerous colour features, such as a correlogram, histogram, Colour Coherence Vector (CCV), and Colour Moments (CM), are offered in the literature. Among these, CM is the simplest and most efficient.

Red-Green-Blue (RGB), Lumnance-Chrominance (YCbCr), Hue-Saturation-Value (HSV), and Hue-Max-Min-Difference (HMMD)are common colour-space methods used in the study. Saturation (S), described by equation 3 determines the degree of colour purity in HSV. If Max (the highest possible value of R, G, or B) is zero, then saturation has a value of 1, otherwise, it is stated as in equation 3.

$$Saturation = \frac{Max - Min}{Max} \qquad [3]$$

Hue (H) determines one colour family with angle0 º to 360º, given by formula 4, and values how bright or dark a colour is, equivalent to the Max value.

$$Hue = \begin{cases} 0, & if\ Max == M \\ 60 * \frac{G-B}{Max-Min}, & if\ Max == R\ and\ G \geq B \\ 360 + \left(60 * \frac{G-B}{Max-Min}\right), & if\ Max == R\ and\ G < B \\ 60 * \left(2.0 + \frac{B-R}{Max-Min}\right), & if\ G == Max \\ 60 * \left(4.0 + \frac{R-G}{Max-Min}\right), & otherwise \end{cases} \qquad [4]$$

According to the matrix in equation 5, YCbCr stands for luminance (Y), blue chrominance (Cb), and red chrominance (Cr):

$$\begin{vmatrix} Y \\ Cb \\ Cr \end{vmatrix} = \begin{vmatrix} 0.299 & 0.587 & 0.114 \\ 0.169 & -0.331 & 0.5 \\ 0.5 & -0.419 & -0.081 \end{vmatrix} \begin{vmatrix} R \\ G \\ B \end{vmatrix} \qquad [5]$$

B. Texture-based

Colour features are only represented by pixels, whereas Texture Features (TF)are represented by groupings of pixels. Texture information is used by the visual system to comprehend and distinguish images. Texture, by definition, describes visually consistent patterns. The two basic types of TF are spatial TF and spectral TF.

Before features can be recovered for the transformed image, spectral TF requires images to be transformed into Frequency Domain (FD), whereas spatial TF retrieves features simply by computing the pixel in the main image. The Gabor filter is often employed for TF extraction since it samples an image's FD by characterising its centre frequency and orientation attributes. Spatial TF extraction is commonly used to segment images [40].

Differences in the spatial structures of geometric or stochastic features are mapped into matching grey values using this method. To hasten the search for an image, researchers have combined texture information with colour features [41].

Like statistical methods, FE approaches can be utilised to extract some elements that would otherwise be difficult to discover [42]. The Grey Level Run Length Matrix, Grey Level Co-occurrence Matrix (GLCM), and Statistical Feature Matrix (SFM) are a few examples. Fourier Power Spectrum (FPS), Gabor wavelet, and Discrete Wavelet Transform(DWT) are examples of transform domain procedures, whereas law mask features are examples of FE signal processing techniques.

C. *Shape-based*

Recognising and identifying physical objects requires the use of shape characteristics (SF). Humans rely heavily on them as a visual cue for checking and matching similarities. You can classify SF as either "region-based" (RB) or "contour-based" (CB). whereas CB establishes SF at the boundary, RB pulls features from the complete object. It has been demonstrated that the Hough Transform (HT) is an effective method for extracting geometric characteristics from objects and for identifying lines and edges. It is useful in fields like pattern analysis, CV, and image processing.

VII. CLASSIFICATION MODEL

Classification is a vital component of PDidentification systems. In the context of this manuscript, categorisation refers to the classification of images of plant leaves based on the ailments they contain. A classifier is trained on images from a training sample before categorising or recognising images from a test set. Many different ML algorithms have been studied for their ability to detect diseases in diverse cultural situations. The classifier must figure out what makes a particular image of a leaf healthy or unhealthy [43]. The two primary types of AI approaches are supervised and unsupervised [44]. The training sample for supervised algorithms includes both inputs and their corresponding outputs. Unsupervised approaches can make intelligent estimates when there are no tagged responses in the training sample. Semi-supervised techniques blend labelled and unlabelled data to train their models. Table II compares the recent work on the AI method of PD classification.

TABLE II. RECENT WORK COMPARISON OF PD CLASSIFICATION USING AI METHOD

Model	**Plant**	**Data**	**Pre-process**	**Segmentation/Feature Extraction**	**Model Validation**
Supervised: YOLOv5 [45]	Money Plant	Kaggle and own data	Normalization Denoising Annotation Outlier Rejection	-	ACC=0.93 PR= 0.75 RE = 0.95
Convolution [46]	Cotton	Kaggle Cotton Leaf and Disease	Augmentation	VGG-16	ACC = 0.99
CNN [47]	Tomato	PlantVillage	Resize K-mean cluster	DWT, PCA, GLCM	ACC =0.99 PR= 0.99 RE= 0.99 F1 = 0.98
Faster-Regionbased CNN [48]	Rice	Kaggle and own data	Annotation	CNN	ACC =0.96 PR= 0.97 SE = 0.96 Dice = 0.96
DenseNetwith RmsProp optimizer[49]	Tomato	Plant Health Open Access Image Library, Plant Village	Resize Denoising Augmentation Outlier Rejection	-	ACC =0.99 PR= 0.99 RE= 0.95 F1 = 0.97

		dataset			
DBNet[50]	Apple	From Northwest A&F University	Not mentioned	CNN	ACC = 0.96
Random Forest[51]	Banana	PlantVillage PSFD-Musa	Resize	Xception	ACC =1.0 PR= 1.0 RE= 1.0 F1 = 1.0
Deep CNN[52]	Potato	Internet and Potato Research Institute of Yunnan Normal University	Augmentation	Mask R-CNN	ACC = 0.97 SP = 0.99 PR = 0.96 RE = 0.95 F1 = 0.95
EfficientNet v2-L [53]	Cardomom	Own, Cardamom Dataset 2021 and PlantVillage	Resize, Outlier Rejection	U2-Net	ACC =0.98 PR= 0.98 RE= 0.98 F1 = 0.98
Novel Light Weight CNN[54]	Multiple	PlantVillage,	Resize	CNN	ACC =0.99 PR= 0.99 RE= 0.99 F1 = 0.99
Conv-3 DCNN [55]	Apple	PlantVillage	Resize Augmentation	CNN	ACC = 0.98
PlantDet[56]	Rice	Kaggle	Resize Normalization Augmentation	-	ACC =0.98 PR = 0.98 RE= 0.98 F1 = 0.8 SP = 0.99
ACC – Accuracy, PR – Precision, RE – Recall, SP – Specificity, SE – Sensitivity, F1 – F1-Score					

VIII. CHALLENGES AND RESEARCH GAP

The challenges of AI-based PD detection using leaf images are detailed in this section.

A. Minimum data set:

PD identification is widely regarded as a niche application for the currently popular AI models used in severalCV applications in the agricultural sector. There is a scarcity of illness samples in agriculture. Self-collected data sets are usually smaller in size and take longer to classify than open standard libraries. Small sample sizes provide the most difficulty in diagnosing PD. Due to the low prevalence and high expense of disease image collection, some PD provides a challenge for the use of AI algorithms in PD diagnosis because there are only a handful of training data sets available[57]. The three options now accessible for dealing with the issue of tiny samples are data amplification, synthesis, and fabrication; transfer learning and fine-tuning of a classical network model; and appropriate network structure design.

B. Problems with lighting:

Previous studies have extensively used indoor light boxes to acquire images of plant pests and diseases [58]. This technique is useful because it reduces image processing complexity by eliminating the effects of ambient light, but the resulting images seem significantly different from those obtained in true daylight. The camera's capacity for handling dynamic light sources is restricted, making it easy for images to be distorted in colour if the lighting source is either too bright or too dim, as is the case with natural light. Additionally, visible properties of PD alter greatly because of a change in view angle and distance in image collection, presenting substantial challenges to the visual identification system.

C. Problems with occlusion:

At the moment, most scientists purposefully avoid detecting plant pests and diseases in complex ecosystems. They are unique in their emphasis on the background. They employ direct intercept of the area of interest to the obtained images, but generally never account for occlusion. When faces are partially hidden, this results in low recognition accuracy and drastically limits their application. Occlusion problems are common in the outdoors. When attempting to diagnose PD, occlusion causes a loss of traits as well as an increase in noise. Recently, researchers [59] have taken on the difficult task of identifying PD in dim lighting, and they've made significant improvements that pave the way for PD recognition to be used in practical settings where AI algorithms are already well-developed. Occlusion, on the other hand, is unpredictable and complicated. Because training the fundamental framework is difficult and hardware device performance remains a limiting issue, we must devote more resources to developing and upgrading the fundamental framework, which involves the development of lightweight

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network architecture. The difficulty of training models should be reduced while maintaining ensuring detection precision and stimulating additional research into GAN and related issues.

D. Speed:

Sluggish Detection Although AI algorithms outperform more traditional approaches, they are also more computationally demanding. Guaranteed detection accuracy, on the other hand, necessitates that the model completely comprehends the image's attributes, which increases the computational load and, as a result, reduces the detection rate, rendering it unsuitable for real-time applications. In most circumstances, minimising the number of calculations required to ensure detection speed is required. Unfortunately, this will result in insufficient training and erroneous or missed detections. As a result, developing a fast and accurate identification system is critical.

IX. CONCLUSION

The majority of Indians rely on agriculture for their livelihood. Farmers have a lot of crop options, but the spread of diseases can severely limit yields. PD are a major contributor to crop failure. The spread of PD poses a serious threat to agricultural productivity and, consequently, to human health. The diseases are generally severe, and they can affect any section of the plant. Due to the cumulative effects of such diseases, they reduce agricultural productivity and raise economic losses. Huge losses in output, time, money, and product quality may result from incorrect PD diagnosis. Monitoring the plant's health at each stage of development is essential for producing a healthy crop. Researchers have been using AI methods to keep tabs on PD and determine how far along in their progression they are. Methods that can forecast the nature of PD would be of great help to farmers. This article sheds light on these methods by presenting the results of a survey covering all aspects of AI-based PD detection using leaf images. Beginning with an examination of several data-gathering platforms, this evaluation focuses down on the best methods for detecting PD. The next section explains the different kinds of processing, segmentation, and feature extraction approaches. Finally, a comparison is made between different methods of classifying PD detection systems using AI. Farmers would benefit from increased crop yield and relief from the problem of hiring an overpriced domain specialist for identifying the disease. There are several areas where the current literature on PD identification is lacking, and they have been identified for future study. Researchers will be able to refine their problem statements after discovering many research holes. The survey article can help novice researchers figure out how to move forward with their studies.

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